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ESSAYS ON CAPABILITY DEVELOPMENT THROUGH ALLIANCES

Kavuşan, Korcan

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Proefschrift

Proefschrift ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. Ph. Eijlander, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op vrijdag 16 januari 2015 om 10.15 uur door

Korcan Kavuşan

geboren op 21 december 1979 te Istanbul, Turkije

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To my wife

PREFACE

This dissertation is the result of my work as a doctoral candidate at the Department of Management and CentER Graduate School at Tilburg University. The four years of my postgraduate training in Tilburg have been challenging, but with the help of many people also very rewarding. This dissertation would not have been possible without the support and guidance of those individuals. I therefore have the following words of appreciation:

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I would like to express my gratitude to all other members of my dissertation committee for evaluating my work and giving me invaluable feedback. Specifically, I would like to thank Xavier Martin for his guidance in the early stages of my doctoral training to structure my research ideas and to rigorously pursue them. I benefited greatly from scholarly works of Brian Silverman and Maurizio Zollo in building my research program, and their work has a profound impact on mine. The confidence of Marius Meeus in my research has reinforced my motivation, and his ideas enabled me to have a deeper understanding of my research areas.

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I need to thank all members of the Management Department and CIR, who have always been supportive and kind to me. In particular, I would like to thank Wolfgang, Ana and Marjolein, who were always available when I needed their support.

I am thankful to my parents and my brother for their unconditional support that enabled me to pursue my life goals. They always made me feel that I am never alone and I cannot appreciate highly enough their role in my personal and professional development.

Last but not least, my immense gratitude goes to my wife Elvan. During the last years she has made more than reasonable sacrifices to enable me to pursue a career in academia. I not only benefited from her emotional support at every stage of my academic endeavors, I also relied on her advice to deal with many professional situations. For these and many other reasons, I would like to dedicate my dissertation to Elvan.

TABLE OF CONTENTS

CHAPTER 1

GENERAL INTRODUCTION

In the last three decades strategic alliances have become a central element in many firms' capability development strategies as they allow firms to rapidly access and utilize new knowledge that is costly and time-consuming to develop internally (Kale and Singh, 2009). This trend is especially prevalent in high-technology industries where shortening product life-cycles and the surging rate of technological innovation motivate firms to rely on external knowledge sources to develop new products and services and to remain competitive (Mowery, Oxley, and Silverman, 1996, 1998; Kale and Singh, 2009). In addition to allowing firms to share the costs and risks of innovation and facilitating rapid entry to foreign markets (Mowery *et al.*, 1996), alliances also enable them to access complementary capabilities (Rothaermel and Boeker, 2008), to increase the efficiency in utilization of their resources (Ahuja, 2000b), and to enhance their market power (Kogut, 1991). Consequently, many firms consider external collaborations as vital complements to internal capability development efforts in their corporate development strategies (Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012).

Concurrent with the increasing importance of alliances, a voluminous literature has emerged that examines how firms can benefit from alliances. Recognizing the role of alliances in facilitating the transfer of tacit knowledge across partnering firms (*e.g.* Mowery *et al.,* 1996; Inkpen, 1998; Inkpen and Dinur, 1998), numerous studies examined how firms can acquire their competitors' knowledge by forming alliances with them (*e.g.* Hamel, Doz, and Prahalad, 1989; Khanna, Gulati, and Nohria, 1998; Dussauge, Garrette, and Mitchell, 2000; for a review see Inkpen and Tsang, 2007). Another stream of studies focused on whether and how alliance experience improves firms' capabilities to manage their subsequent alliances (*e.g.* Anand and Khanna, 2000; Zollo, Reuer, and Singh, 2002; Sampson, 2005) as well as their acquisitions (Porrini, 2004; Kale and Singh, 2009; Zollo and Reuer, 2010). Recognizing that many firms engage in multiple simultaneous alliances, researchers recently began analyzing firms' alliances as a portfolio rather than in isolation (*e.g.* Parise and Casher, 2003; Hoffmann, 2007; Lavie and Miller, 2008; for a review see Wassmer, 2010), pointing at the need to understand the implications of alliances to partnering firms beyond the single alliance level (Kale and Singh, 2009).

While the current literature provides valuable insights to benefits of alliances for partnering firms, there are several areas in which theoretical explanations and empirical evidence are rather scarce. First, while research on alliance portfolios provides new and valuable insights to management and performance implications of alliance portfolios (*e.g.* Heimeriks and Duysters, 2007; Lavie, 2007), we know relatively little about the factors that lead firms to alter the configurations of their alliance portfolios over time (Wassmer, 2010). Second, while many firms join alliances to acquire knowledge from their alliance partners, alliances also allow partnering firms apply their complementary knowledge bases toward a joint outcome, without knowledge acquisition being a primary goal (Mowery *et al.*, 1996; Nakamura, Shaver, and Yeung, 1996; Grant and Baden-Fuller, 2004; Inkpen and Tsang, 2007). These alliances are motivated by complementary specialization rather than knowledge acquisition because each partner focuses on its own area of expertise. Although complementary specialization is a commonly utilized alliance strategy in many high-technology industries, it received scant scholarly attention and its antecedents and consequences are not as thoroughly known as those of knowledge acquisition. Third, although current research demonstrates that alliance experience can teach firms how to manage acquisitions by transferring their alliance management practices to their acquisitions, studies in this area consider alliance experience as a homogenous construct, ignoring heterogeneities in terms of management practices among a firm's previous alliances.

In an attempt to improve the understanding of strategic alliances and their benefits to partnering firms, the three studies in this dissertation provide theoretical explanations and empirical evidence in these under-researched yet theoretically and managerially important areas. I begin by examining firm's how alliance portfolios evolve over time. As a firm's alliance portfolio is ultimately shaped by the characteristics of each incremental alliance, I investigate how a firm choses its partner and the focal technological area in its newly formed alliances, with respect to alliances already in its portfolio.

Alliance portfolio evolution

A firm that makes its alliance formation decisions with a portfolio approach and builds a coherent alliance portfolio can realize synergistic gains by leveraging knowledge across the partners within the portfolio (Duysters, 1999; Wassmer, 2010). Each alliance formation decision requires a firm to make choices about the partner (*e.g.*, whether to ally with an existing partner or with a novel one), governance mechanisms, and scope of the alliance. Such decisions about a firm's individual alliances collectively determine the configuration of its alliance portfolio (Wassmer, 2010). This configuration is directly related to a firm's value generation potential from its set of partnerships as it determines "*the position of the focal firm in the interorganizational field and the quality and quantity of external resources to which the focal firm has access*" (Hoffmann, 2007 p.830). Recognizing this importance, numerous studies examined how firms should configure their alliance portfolios so as to maximize the value generated through their external collaborations (*e.g.* Parise and Casher, 2003; Hoffmann, 2007; Lahiri and Narayanan, 2013). However, empirical evidence suggests that for many firms alliance portfolios evolve into a random collection of alliances rather than a coherent portfolio (Bamford and Ernst, 2002; Kale and Singh, 2009).

A possible reason why the insights from these prescriptive studies are not adequately reflected in firms' patterns of alliance activities is that these studies implicitly assume that firms make alliance formation decisions rationally as parts of an overall corporate development strategy, whereas in reality firms may be making such decisions as a response to other short-term stimuli (Wassmer, 2010). Although the understanding of how alliance portfolios should evolve is relatively well-developed, theoretical insights and empirical evidence regarding how they actually evolve remain limited. In Chapter 2 I address this issue, and examine how performance feedback (performance relative to aspiration levels) influences alliance portfolio decisions. Drawing on the behavioral theory of the firm (Cyert and March, 1963), a substantial body of literature (*e.g.* Bromiley, 1991; Greve, 2003a; Baum *et al.*, 2005; Audia and Greve, 2006) demonstrates that performance feedback affects many organizational decisions such as alliance formations. Consistent with this line of research, I argue and find that while divergence from performance aspirations motivates risk-taking in alliance portfolio decisions, the type and nature of the risk a firm assumes differs depending on weather the firm performs above or below its aspirations.

As emphasized by research on alliance portfolios, alliances are important instruments with which firms can access and utilize new knowledge, especially in high-technology industries. While external technological knowledge utilization through alliances can be expected to influence alliance partners' technological capabilities, the nature of such influence varies across alliances (Nakamura *et al.*, 1996). While some alliances facilitate knowledge acquisition between partnering firms, increasing the similarity between their technological capability portfolios, others allow partnering firms to specialize in complementary areas, resulting in more dissimilar but complementary capabilities. In the third chapter of the dissertation, I distinguish between knowledge acquisition and complementary specialization as alternative knowledge utilization strategies in alliances, and perform a comparative analysis of these strategies in terms of their antecedents.

Knowledge utilization in alliances

While many firms consider the cooperation mechanisms provided by alliances as conduits to acquire knowledge from their partners, knowledge acquisition may not always be a feasible or desirable goal in alliances for several reasons. First, if the knowledge that a firm seeks to acquire is highly tacit or complex, it may not be effectively transferred without acquiring the organizational unit in which that knowledge resides (Huber, 1991). Second, competitive pressures to continuously introduce new products and services may leave firms little time to successfully acquire their alliance partners' knowledge and convert it to commercial outcomes, which is a time-consuming process (Lubatkin, Florin, and Lane, 2001). In addition, firms may be unwilling to share knowledge with competing alliance partners if they perceive that their partners are benefiting more from the alliance (Khanna *et al.*, 1998). Complementary specialization is an effective alternative external knowledge utilization strategy for firms to respond to these challenges. This strategy does not only allow alliance partners to benefit from each other's knowledge without incurring the costs of acquiring that knowledge, it also enables firms to exploit their own competences by targeting their innovative efforts to their respective areas of expertise, rather than to internally replicating each other's knowledge.

Research on external knowledge utilization through alliances traditionally considered knowledge acquisition as the primary knowledge utilization outcome sought by firms, and identified factors which enhance knowledge acquisition from alliance partners such as technological overlap (*e.g.* Mowery *et al.*, 1996; Mowery, Oxley, and Silverman, 2002) and prior alliance experience (*e.g.* Sampson, 2005). Although technological overlap and alliance experience are widely recognized to enhance interfirm collaboration and knowledge utilization in alliances, their impact on alternative knowledge utilization outcomes, such as complementary specialization, has not been thoroughly researched. While Mowery *et al.* (2002) show that technological overlap enhances both knowledge acquisition and complementary specialization in alliances, the understanding of how these commonly recognized antecedents of external knowledge utilization influence complementary specialization, in comparison to knowledge acquisition, in alliances remains limited. I discuss these issues in Chapter 3. I argue and find empirical support that while technological overlap between alliance partners enhances complementary specialization within an alliance, prior alliance experience is conducive to interpartner knowledge acquisition.

An emerging stream of research suggests that the outcomes of alliances also influence firms' other organizational activities. More specifically, as a firm accumulates experience in alliances, the actions and procedures used to manage its alliances are stored in its organizational memory and transferred to similar future organizational events, such as acquisitions (Porrini, 2004; Kale and Singh, 2009; Zollo and Reuer, 2010). In the fourth chapter of the dissertation I examine how a firm's experience in knowledge acquisition and complementary specialization alliances influences the management and performance of its acquisitions.

Alliance experience and acquisitions

As the importance of external sources for firms' capability development increases, acquisitions in addition to alliances have become a prominent strategy for many firms (Haleblian *et al.*, 2009; Makri, Hitt, and Lane, 2010). After having experienced a setback following the global financial crisis in 2008, acquisition activity resumes to grow with firms worldwide spending 2.91 trillion US dollars in 2013 for acquisitions (Dealogic, 2014). Despite this economic importance, many firms struggle to manage their acquisitions, and most acquisitions fail to create shareholder value (Barkema and Schijven, 2008). Intrigued by this paradox, scholars examined how firms can learn to manage their acquisitions and found that experience in acquisitions as well as in other similar organization activities, such as alliances, influence subsequent acquisition performance (for a review see Barkema and Schijven, 2008). This research stream demonstrates that the influence of past organizational activities on the performance of subsequent ones depends on the extent to which the past and subsequent activities require similar management practices (*e.g.* Finkelstein and Haleblian, 2002; Haleblian *et al.*, 2009). Thus, scholars investigating the relationship between alliance experience and acquisition performance focused their efforts on identifying acquisition contexts in which the management practices developed in alliances are applicable (Porrini, 2004; Zollo and Reuer, 2010).

An important shortcoming of these studies is that they consider alliance experience as a homogenous construct and assume that all alliances are managed similarly. Alliances however differ in terms of their management practices, depending on their strategic goals. For instance, knowledge acquisition alliances require partnering firms to collaborate more closely than complementary specialization alliances (Mowery *et al.*, 2002). While the managerial challenge for partnering firms in knowledge acquisition alliances is to coordinate their joint operations, in complementary specialization alliances it is to align their alliance-related activities while maintaining their autonomous operations (Lui, 2009). Experience in these different types of alliances therefore equips firms with different managerial skills, which may impact differently the management and performance of their future acquisitions. In Chapter 4 I examine these differential effects. I find that the influence of experience in knowledge acquisition and complementary specialization alliances on the performance of future acquisitions depends on the degree of autonomy required in the management of these acquisitions.

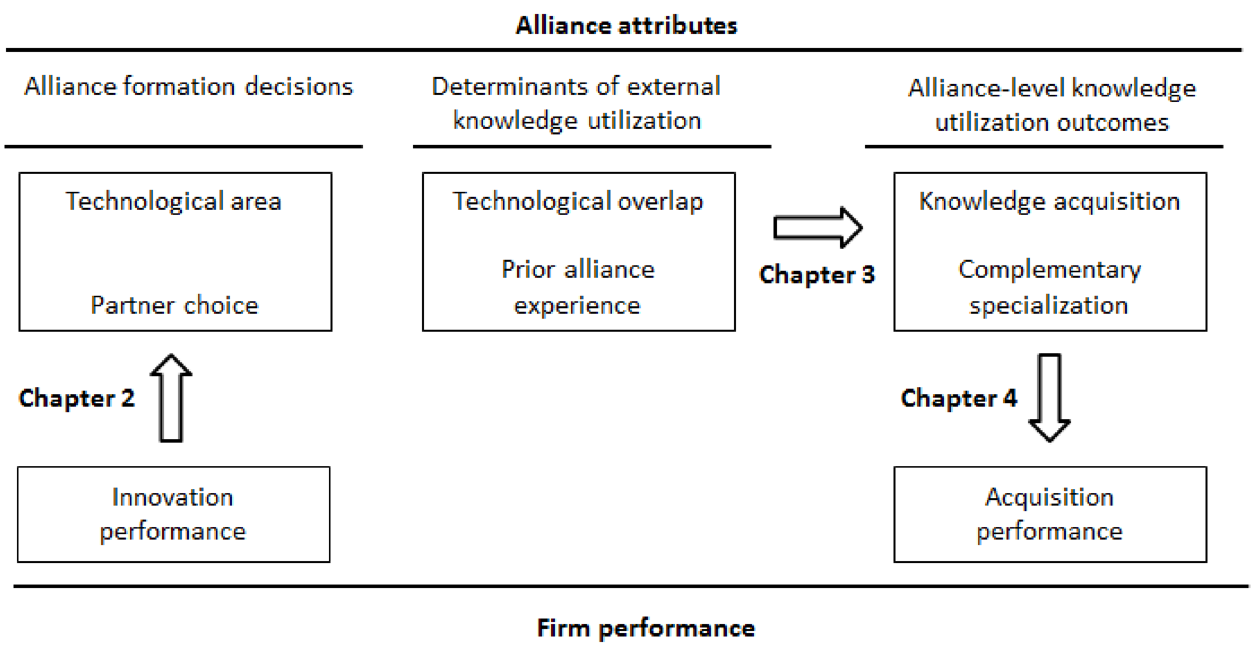
Capability development through alliances

While alliances are of vital importance to many firms to develop new capabilities, they also inflict substantial economic and managerial costs to firms (*e.g.* Pisano, 2006 p.180), which makes effective design and management of alliance strategies crucial. Nevertheless, recent research suggests that firms often fail to realize the potential benefits of their alliances (Kale and Singh, 2009 p.45). Given the vast amount of literature on formation and management of alliances this finding is remarkable and provides two important insights. First, managers need more precise guidance to carry out alliance activities. Second, research on alliances should be more closely aligned with practice. Taken together, the three studies in this dissertation attempt to make contributions in both areas.

I believe that understanding the antecedents of actual firm behavior is important to bring theories on alliance strategies closer to practice (Powell, Lovallo, and Fox, 2011), and take a behavioral approach (Cyert and March, 1963) in Chapter 2 to examine the evolution of firms' alliance activities over time. By shedding light on how a firm's performance relative to its aspirations affects its alliance formation decisions, this study can help managers to become more self-reflective in making these decisions, and aid corporate stakeholders in interpreting and evaluating managerial behavior. In Chapters 3 and 4 I compare two alternative external knowledge utilization strategies, knowledge acquisition and complementary specialization, in terms of their antecedents as well as their implications for management of subsequent acquisitions. Jointly, these studies contribute to and bridge the research streams in organizational learning in alliances on the one hand (*e.g.* Mowery *et al.*, 1996, 2002; Inkpen and Tsang, 2007), and experience spillovers across alliances and acquisitions on the other (Porrini, 2004; Zollo and Reuer, 2010). The central insight of these chapters is that firms should consider their alliances as parts of an overall corporate development strategy, rather than isolated events driven by short-term objectives. To aid managers in doing so, the findings of these studies provide precise advice as to how firms can equip themselves with necessary skills to realize their knowledge utilization goals in their alliances and how they can leverage their experience in alliances to manage their acquisitions.

As tapping into external knowledge sources for capability development is becoming increasingly important, firms increase their reliance on strategic alliances to enhance their competitiveness (Kale and Singh, 2009 p.45). Therefore, the need for scholarly research to understand, explain and guide firms' alliance activities, as well as their implications on different dimensions of firm performance is greater than before. The goal of this dissertation is to take the research in this area one step further. Collectively, the three studies in this dissertation examine the relationships between various alliance attributes such as partner choice, technological focus, and different knowledge utilization outcomes on the one hand, and two dimensions of firm performance, namely performance in acquisitions and in generating innovation output, on the other, as shown in Figure 1. In doing so, the three studies underscore that while a firm's alliances influence its performance outcomes; performance outcomes also shape its alliance activities. My findings offer insights to improve the understanding and management of strategic alliances, as well as to enhance innovation through interfirm collaboration, thereby providing actionable guidelines to managers and other corporate stakeholders in shaping the corporate development strategies of their firms.

Figure 1 – Alliance attributes and firm performance



CHAPTER 2

PERFORMANCE FEEDBACK AND ALLIANCE PORTFOLIO RECONFIGURATION

ABSTRACT

We develop performance feedback models to examine when and how firms simultaneously reconfigure the technological scope and partner mix of their alliance portfolios following an assessment of firm performance relative to aspirations. Analysis of panel data on U.S. biotechnology firms, 1981-2000, shows that below-aspiration performance is associated with the formation of alliances with novel partners within the technological scope of the existing alliance portfolio. In contrast, above-aspiration performance is associated with the formation of alliances with existing partners outside the technological scope of the existing alliance portfolio. Finally, results show evidence of inertia below aspirations, in that firms' greater equity commitments to their existing alliance partners diminish their propensity to form alliances with novel partners.

Keywords: Alliances, performance feedback, alliance portfolio, innovation performance, biotechnology

INTRODUCTION

In line with the increasing prevalence of interfirm alliances to tap into outside knowledge sources, many firms simultaneously engage in multiple alliances with different partners to improve their innovation performance (Wassmer, 2010). Recognizing this fact, recent studies have begun to analyze firms' alliance activities from a portfolio perspective (Parise and Casher, 2003; *e.g.* Hoffmann, 2007; Lavie, 2007; Lavie and Miller, 2008; see Wassmer, 2010 for a review), emphasizing the need to understand the management, evolution, and performance implications of alliances beyond the single alliance level. While research in this stream provides new and valuable insights regarding the management and performance implications of alliance portfolios, the evolution and reconfiguration of alliance portfolios has received much less scholarly attention to date. More specifically, we know little about what leads firms to reconfigure their alliance portfolios over time (Wassmer, 2010).

Although studies linking firm performance to various alliance portfolio characteristics, such as partner diversity (Jiang, Tao, and Santoro, 2010) and technological scope (Vasudeva and Anand, 2011), provide insights regarding performance-enhancing alliance portfolio configurations, research also suggests that few firms manage their alliances as a coherent portfolio and many firms fail to configure their alliance portfolios to unlock their full potential (Bamford and Ernst, 2002; Kale and Singh, 2009). It thus appears that the practical implications of insights from alliance portfolio research on firms` alliance activities remain rather limited. Exploring the factors that lead firms to alter the configuration of their alliance portfolios is therefore an important endeavor to understand the antecedents of firm behavior that shapes alliance portfolios.

We draw on performance feedback theory (Cyert and March, 1963; Greve, 2003a) to propose and test a conceptual framework of when and how firms reconfigure their alliance portfolio over time. Performance feedback theory argues that decisions about organizational actions are a function of firm performance relative to an aspiration level, *i.e.*, a measurable anchoring point on a relevant performance variable that defines the boundary between perceived success and failure (March and Simon, 1958; Cyert and March, 1963; Greve, 2003a), based on a firm's historical performance or the performance of other comparable firms (Levinthal and March, 1981; Greve, 2003a p.42-48 ; Bromiley and Harris, 2014). Performance away from the aspiration level is believed to increase the likelihood of risky search, though the nature and domain of search may be distinct depending on whether it is prompted by perceived failures or successes (*e.g.* Cyert and March, 1963; Greve, 2003a). Building on this key insight, we use performance feedback theory to examine how performance below and above aspirations has distinct implications for how firms reconfigure their alliance portfolios over time. This theory presents a suitable theoretical approach to study the reconfiguration of alliance portfolios because a comparison of performance to pre-existing aspiration levels offers an intuitive heuristic to boundedly-rational actors, which helps categorize recent firm performance as either a perceived success or a failure, in turn generating implications for the extent and domain of risky organizational actions such as decisions about alliance portfolio reconfiguration. We specifically focus on innovation performance, because, given the prominence of R&D alliances in many firms' competitive strategies, we believe that this performance measure is more directly related to firms' alliance activities than financial or accounting performance measures.

While the configuration of alliance portfolios can be captured in a number of ways, alliance portfolios mainly evolve along three dimensions as a result of firms' decisions about partner choice, scope of activities, and governance mode in each of their alliances (Jiang *et al.*, 2010; Lavie, Kang, and Rosenkopf, 2011; Duysters *et al.*, 2012). Among these three dimensions, the first two are shown by the literature to influence innovation performance: While alliance portfolio technological scope directly affects innovation performance through its impact on firms' absorptive capacities (Vasudeva and Anand, 2011), partner choice has indirect effects by enabling firms to tap into novel knowledge sources (Baum *et al.*, 2005). We therefore focus our attention here on two alliance portfolio dimensions, namely the portfolio's *technological scope* (the number of distinct technological areas covered across all of a firm's alliances) and *partner mix* (the mix of novel and repeat partners). Specifically, we focus on how firms make simultaneous decisions about technological scope and partner choice in their newly formed alliances, with respect to the existing technological scope and partner mix of their alliance portfolios, as a result of performance feedback.

We propose and find that when firms perform below aspirations, they form new alliances with novel partners, yet within the existing technological scope of their alliance portfolios. In contrast, when performance exceeds aspirations, firms form new alliances outside the technological scope of their alliance portfolios, yet with existing alliance partners. We further find that the strength of a firm's equity commitments to its existing alliance partners (the governance dimension of the alliance portfolio) decreases its propensity to form new alliances with novel partners, consistent with the organizational inertia perspective (Hannan and Freeman, 1977; Kim, Oh, and Swaminathan, 2006). By examining how firms simultaneously change these alliance- and partner-level attributes in response to performance feedback, we complement prior studies that have focused on the determinants of distinct portfolio dimensions in isolation (*e.g.* Beckman, Haunschild, and Phillips, 2004; Baum *et al.*, 2005; Lavie and Rosenkopf, 2006). More specifically, we advance the understanding of alliance portfolio dynamics by proposing that decisions concerning portfolio technological scope and partner mix are made jointly (cf. Wassmer, 2010 p.164) and, therefore, are likely to share common antecedents. We also contribute to performance feedback theory by offering a theoretical explanation for the difference in the nature and type of risk-taking occurring when performance is below or above aspirations. Finally, we are among the first to highlight how inertia may play a role in the performance feedback cycle that shapes alliance portfolio reconfiguration.

THEORY AND HYPOTHESES

Below-aspiration performance and alliance portfolio reconfiguration

Performance below aspirations triggers "problemistic search", a goal-oriented behavior focused on solving an organizational problem so as to raise performance to the firm's aspiration level (Cyert and March, 1963; Levinthal and March, 1981). When performance is slightly below aspirations, a firm will search for solutions "*near the problem symptom or the current activities*" (Greve, 2003a p.56) in order to achieve small improvements necessary to improve performance. However, when performance is far below aspirations, the likelihood that appropriate solutions to an organizational problem are found locally decreases, forcing firms to consider more risky, exploratory search behaviors instead (Bromiley, 1991; Greve, 2003a). Problemistic search in response to performance below aspirations has been observed in a wide range of organizational behaviors and settings (for an integrative review see Greve, 2003a). From the innovation performance point of view, problemistic search corresponds to organizational actions which can improve firms' innovation output and increase it to the aspired level. While innovation output is influenced by firms' internal R&D efforts as well as their alliances (Hagedoorn and Wang, 2012), we focus on the latter because our goal is to examine firms' alliance portfolio reconfiguration choices as a result of their search behaviors in response to performance feedback.

Problemistic search in response to a negative discrepancy between aspired and realized innovation performance motivates firms to modify their strategies and assumptions about their R&D efforts, to address performance problems. As alliances constitute important elements of a firm's innovation efforts, below-aspiration innovation performance is likely to lead firms to make more risky but potentially more rewarding choices about technological scope and partner choice, two factors that are recognized by the literature to influence the innovation outcomes of alliances, in their newly formed alliances with respect to the technological scope and partner mix of their existing alliance portfolios.

When deciding on the technological scope in a newly formed alliance, a firm performing below its aspirations faces two risky alternatives: On the one hand, focusing on a technological area in which the firm has already an alliance in its existing alliance portfolio means investing in a potentially promising area that has failed to generate a satisfactory level of innovation output. On the other hand, focusing on a novel technological area may expose the firm to greater uncertainties both in terms of the eventual innovation outcomes and in terms of the time period needed to realize these outcomes (Pisano, 2006). While exploration of new technologies can enhance innovation performance in the long run, it is unlikely to result in the immediate performance improvements which problemistic search is expected to yield because exploratory R&D typically requires long lead times before starting to contribute to firms' innovation performance (March, 1991; Greve, 2003a). Firms engaged in problemistic search however require more immediate performance improvements (Lehman *et al.*, 2011), which are more likely to be realized by increasing attention to solving problems in their existing technological areas. The problem-oriented nature of problemistic search is widely established in the literature. Levinthal and March (1981 p.309) for example state that "[*problemistic] search emphasizes relatively immediate refinements in the existing technology, greater efficiency, and discoveries in the near neighborhood of the present activities.*" We therefore suggest that, consistent with the literature on risk-taking (Greve, 2003b p.27), because focusing in new technological areas represents a higher-risk alternative to achieve immediate performance improvements with more uncertain returns, problemistic search will lead firms to form new alliances on their existing technological areas and seek solutions to performance problems within these areas.

One such solution that firms may consider is to engage with alliance partners they are not currently collaborating with (*e.g.* Beckman *et al.*, 2004; Baum *et al.*, 2005; Lavie and Rosenkopf, 2006). On the one hand, due to incomplete information about the reliability, motives, and capabilities of such novel partners, they present a risky and uncertain alternative compared to engaging existing partners (Baum *et al.*, 2005). Moreover, firms may need time to develop patterns of interaction with novel partners (Zollo *et al.*, 2002; Gulati, Lavie, and Singh, 2009). On the other hand, novel partners have the potential to offer fresh perspectives on technological problems within the firm's existing scope of activities, which may in turn help the firm reduce the discrepancy between innovation performance and aspirations. When performance is below aspirations, the perceived benefits of novel partners may thus outweigh the greater risk and uncertainty that such partners entail (Baum *et al.*, 2005). Although establishing smooth relationships with novel alliance partners is a time-consuming process, a focal firm, due to its familiarity with the technological area covered by the alliance, may consider the relational uncertainties of allying with new partners as a lesser threat to obtaining immediate performance improvements than the technological uncertainties and long lead times associated with exploring new technological areas

These arguments suggest that below aspirations, firms become more likely to form alliances with novel partners, yet within the technological areas in which they operate, thus remaining within the technological scope of its alliance portfolio. This approach blends the opportunity for fresh perspectives associated with the engagement of novel alliance partners with the redundancy benefits of remaining within the technological scope of the existing alliance portfolio. Redundancy in technological scope across a firm's existing and new alliances is likely to increase competition across its partners in these alliances, giving the firm the opportunity to play novel and existing partners against each other, while also attenuating partners' opportunistic behaviors (Lavie, 2007). These benefits will together increase the likelihood that suitable solutions become available to the firm, and help the firm raise its performance toward its aspirations. Overall, therefore, we predict that in the failure range, firms *will not* reconfigure the technological scope of their alliance portfolios, while they *will* reconfigure their partner mix, by forming alliances with novel partners.

Hypothesis 1: The further a firm's innovation performance is below aspirations, the greater its propensity for the formation of alliances within the existing technological scope of that firm's alliance portfolio with novel partners.

The moderating role of alliance portfolio commitment

Though Hypothesis 1 predicts an increase in the motivation for risky search when performance decreases relative to aspirations, the organizational inertia perspective (*e.g.* Hannan and Freeman, 1977) suggests that performance shortfalls are likely to generate distinct responses depending on the level of inertia implicated in a firm's existing alliance portfolio (cf. Greve, 2003a). One prevalent source of inertia is the scale of a firm's involvement in the alliances within its existing portfolio (Kim *et al.*, 2006) *i.e.* a firm's monetary and organizational commitment to its existing alliances. A firm has a choice between relatively low-commitment alliances, such as contractual agreements, and high-commitment alliances, such as those containing minority equity investments and joint ventures (*e.g.* Gulati and Singh, 1998). We propose that a greater prevalence of high-commitment alliances within a firm's existing portfolio, *i.e.*, greater alliance portfolio commitment, induces inertia, making the firm inherently less likely to reconfigure its portfolio when innovation performance is below aspirations.

Greater portfolio commitment means that a firm and its partners are more interdependent and the partners to whom a firm is more committed have a greater voice in the firm's decision making process. Moreover, such voice is likely to be stronger when the firm engages in actions that may undermine the activities in alliances with such partners (Gimeno, 2004). A firm's decision to engage novel partners within the existing portfolio's technological scope represents a portfolio reconfiguration decision particularly likely to be perceived by a firm's existing partners as cannibalizing the value of their alliances with the firm. Indeed, especially this competitive kind of alliance formation may "*place explicit or implicit restrictions on the resources that a business devotes to older relationships*" (Singh and Mitchell, 1996 p.102) and is likely to shift the balance of power between a firm and its partners in favor of the focal firm (Lavie, 2007). In this case, a firm's existing partners have an incentive to respond negatively to the firm's plans to reconfigure its alliance portfolio (Duysters and Lemmens, 2003), and such negative responses will increase with the prevalence of high-commitment alliances in the firm's portfolio. Thus, in the failure range, the likelihood of portfolio reconfiguration will be affected by the level of a firm's alliance portfolio commitment as follows:

Hypothesis 2: When performance is below aspirations, the greater a firm's alliance portfolio commitment, the smaller its propensity for the formation of alliances with novel partners within the existing technological scope of that firm's alliance portfolio.

Above-aspiration performance and alliance portfolio reconfiguration

When a firm's innovation performance is above aspirations, the likelihood of problemistic search will decrease (Greve, 2003a). At the same time, above-aspiration performance is likely to increase the accumulation of organizational slack, which will in turn motivate "slack search" (Cyert and March, 1963; Singh, 1986). Innovation performance above aspirations may not only free employee time and capital, and relax coordination and control pressures (March 1994); it may also increase a firm's ability to attract additional resources (*e.g.* Hall, Jaffe, and Trajtenberg, 2005; Sood and Tellis, 2008). Moreover, recent successes may boost a firm's confidence necessary to pursue actions with high potential pay-offs, but previously believed to be too risky (Baum *et al.*, 2005). Taken together, when performance is above aspirations, accumulated slack may progressively motivate firms to explore new areas which may potentially yield profitable outcomes, rather than to engage in risky behaviors in areas that are related to any existing organizational problem. As a starting point, therefore, we propose that when performance increases relative to aspirations, firms will be more likely to engage in new alliances in technological areas beyond the scope of their existing alliance portfolio (Levinthal and March, 1981)

While slack search will spark experimentation in novel technological areas, it is unlikely to be completely immune to pressures for managerial accountability (Cyert and March, 1963). We thus propose that while slack search may change the technological areas in which a firm engages in alliance activities, such change is less likely with respect to the partners it collaborates with. Above-aspiration performance implies that interactions with existing partners have been successful and, compared to the formation of new alliances with novel partners, alliance formation with existing partners is much less subject to concerns related to cooperative incentives and coordination challenges (Gulati and Singh, 1998; Zollo *et al.*, 2002). Li and Rowley (2002), for example, find that firms are especially likely to renew alliances with existing partners if prior alliances with such partners were successful rather than unsuccessful, while Gulati *et al.* (2009) show that considerable cumulative abnormal returns accrue to firms announcing a new alliance with an existing partner.

Though in the failure range firms may believe that the problem-specific benefits of novel partners outweigh the costs related to incentive and coordination issues, in the success range this may not be the case. In knowledge intensive industries in particular, the costs associated with an unjustified change in alliance partners may be especially steep, given the time involved both in negotiating an agreement and in developing the mutual trust and relational routines (Gulati, 1995; Zollo *et al.*, 2002) necessary to begin to engage in the exploration activities that slack search is expected to stimulate. The simultaneous reconfiguration of both the technological scope and partner mix of a firm's alliance portfolio thus would appear to generate inherent managerial challenges and an exposure to perhaps excessive risk (Lavie *et al.*, 2011), which may in turn lead relevant audiences, such as investors, to question the reliability and accountability of the firm (Hannan and Freeman, 1984). Therefore, our arguments suggest that when performance is above aspirations, firms *will* reconfigure the technological scope of their alliance portfolios, but they *will not* reconfigure their partner mix.

> *Hypothesis 3: The further a firm's innovation performance is above aspirations, the greater its propensity for the formation of alliances with existing partners outside the existing technological scope of that firm's alliance portfolio.*

Overall, our conceptual framework generates predictions on alliance portfolio reconfiguration that are jointly consistent both with the implications of performance feedback theory (Cyert and March, 1963; Greve, 2003a) and with pressures on firms for reliability and accountability (Hannan and Freeman, 1984). Building on the insight that the nature (*i.e.* problemistic or slack search) and domain (technological scope or partner choice) of search may be distinct depending on whether it is prompted by perceived failures or successes, we predict that a firm reconfigures its alliance portfolio's partner mix but not technological scope below aspirations, while reconfiguring its portfolio's technological scope but not partner mix above aspirations. Therefore, when performance moves from the failure to the success range, our theory predicts that firms will refocus their risky search behavior from the partner domain toward the technology domain.

While our predictions only focus on alliance portfolio reconfiguration through new alliance formations in existing technological areas with new partners and in new technological areas with existing partners, these portfolio reconfiguration scenarios are not exhaustive. It could be argued for example that firms performing significantly below aspirations would form alliances with new partners in novel technological areas (thus engaging in risky search in both partner mix and technology domains), and firms performing at their aspiration levels would form alliances with existing partners in their existing technological areas (thus refraining from risky behaviors in either domain). Following Lavie and Rosenkopf (2006), we however posit that simultaneous reconfiguration in multiple domains would generate a tension between the urge to access new knowledge that pressures firms toward forming alliances in new technological areas and with new partners (*e.g.* Rothaermel and Boeker, 2008), and organizational inertia (Hannan and Freeman, 1984) that impels firms toward forming alliances in existing technological areas and with existing partners. We therefore suggest that, as a result of a balance between these conflicting organizational pressures, firms will limit their risky search behavior to either technology or partner mix domains of their alliance portfolios (Lavie and Rosenkopf, 2006; Lavie *et al.*, 2011), and present a behavioral perspective explaining when and why they configure either domain.

DATA AND METHODS

Sample and data collection

We test our hypotheses on a sample of listed U.S. biotechnology firms engaged in alliances during 1981-2000. Although many large pharmaceutical firms as well as some food and agricultural firms have been involved in biotechnology since its emergence in the late 1970s, the central players in this industry are dedicated biotechnology firms (DBFs; Powell, 1996; Pisano, 2006). To share the costs and reduce the risks of drug development, DBFs actively engage in collaborations with each other as well as with large pharmaceutical firms (Stuart, Hoang, and Hybels, 1999; Pisano, 2006). Because of high capital requirements, large numbers of potentially useful technological methods, and high degrees of uncertainty in drug R&D, alliances play an important role for the success and survival of DBFs (Pisano, 2006; van der Valk, Moors, and Meeus, 2009). These firms therefore constitute an ideal setting for our study.

Following Gulati and Higgins (2003) and Higgins and Gulati (2006), we obtain our initial sample of public U.S.-based DBFs from the *BioWorld Stock Report for Public Biotechnology Companies* in 2001. This listing solely includes DBFs and excludes large corporations with primary activities outside of biotechnology, thus constituting an appropriate data source for our study. We then identify all alliances formed by these firms between 1981 and 2000 using the Recombinant Capital (RECAP) database, which is commonly used for research in pharmaceutical and biotechnology industries as it includes in-depth information such as press releases and legal contracts for alliances and acquisitions. We collect further data on our sample firms from their annual reports, from COMPUSTAT, and from U.S. patent information to measure their performance and aspiration levels from the NBER Patent Data Project (Hall, Jaffe, and Trajtenberg, 2001).

Because our key interest is in estimating models of alliance portfolio reconfiguration, rather than portfolio configuration per se, we use information on alliance formation during 1981-1984 to construct initial alliance portfolios for all sample firms that formed alliances during this time window. In so doing, we also alleviate concerns of left-censoring. We subsequently update firms' alliance portfolios annually using this rolling four-year window, assuming that alliances formed by a firm in a given year continue to exist some years into the future. Our choice of focusing on alliances four years preceding an observation year is consistent with prior research, which generally considers five years to be the average period in which an alliance contributes to a firm's capability development (*e.g.* Heimeriks and Duysters, 2007).

After excluding firms that underwent corporate restructuring during our sampling period, and those with missing data on one or more of the variables, we obtain a final panel dataset comprised of 185 DBFs for a total of 1,138 firm-year observations. This dataset form the basis for our empirical models predicting alliance portfolio reconfiguration in the years from 1985 to 2000. The panel is unbalanced, reflecting a substantial increase in the number of DBFs entering into alliances during the sampling period (*e.g.* Powell *et al.*, 2005; Roijakkers and Hagedoorn, 2006). Because our estimation procedure excludes firms with no non-zero entries on the dependent variable, our models include between 189 and 988 firm-year observations, determined by each dependent variable.

Dependent variables

We specify our dependent variables so as to capture both the nature of the technological areas (*i.e.* existing within a firm's alliance portfolio or novel) and the nature of the partners (*i.e.* existing or novel) in a firm's newly formed alliances in a given year. We generate three pairs of dependent variables to enable us to perform a stepwise assessment of our hypotheses. Two pairs of dependent variables capture the change in alliance portfolio technological scope and partner mix separately. The third pair captures combinations of the two.

The first pair of dependent variables captures the change in alliance portfolio technological scope. The RECAP database lists all technological areas (such as monoclonals, recombinant DNA and transgenics), if applicable, that are covered in alliances recorded in the database. In total 53 distinct technological areas are covered by the alliances in our dataset. To construct our dependent variables measuring technological scope, we compare for each firm in our sample the technological areas covered by that firm's alliances in a focal year to technological areas covered by its alliances in four years preceding the focal year (its alliance portfolio). Specifically, *Alliances in existing technologies* measures the number of a focal firm's alliances formed in the year *t+1* which only focus on such technological areas that are already covered by that firm's existing alliances in its alliance portfolio. Similarly, *Alliances in novel technologies* measures the number of a focal firm's alliances formed in the year *t+1* which focus on at least one technological area that is not covered by that firm's existing alliances in its alliance portfolio.

The second pair of dependent variables captures the nature of the partners in a firm's newly-formed alliances. Specifically *Alliances with existing partners* measures the number of a focal firm's alliances formed in the year *t+1* with its existing alliance partners. Similarly, *Alliances with novel partners* measures the number of a focal firm's alliances formed in the year *t+1* with novel alliance partners.

Since our hypotheses predict a simultaneous change in alliance portfolio technological scope and partner mix, we construct a third pair of dependent variables that captures the changes in these areas simultaneously. *Alliances in existing technologies with novel partners* measures the number of a focal firm's newly-formed alliances in year *t*+1 with novel alliance partners which only focus on technological areas that are already covered by that firm's existing alliance portfolio (within its alliance portfolio technological scope). We test H1 with this dependent variable. To test H2, we interact this variable with the *Alliance portfolio commitment* variable. Our last dependent variable *Alliances in novel technologies with existing partners* measures the number of a focal firm's newly-formed alliances in year *t*+1 with its existing alliance partners which focus on at least one technological area that is not covered by that firm's existing alliance portfolio (outside of its alliance portfolio technological scope). We test H3 with this dependent variable.

Independent variables

We construct our independent variables as the difference between a focal firm's actual innovation performance in year *t* and its performance aspiration levels. We rely on the patenting activities of the DBFs in our sample to calculate their innovation performance and to construct their historical and social aspiration levels. Patents have the potential to protect competitive advantage in biotechnology because they offer effective intellectual property protection necessary for firms to bring novel technologies to market (Levin *et al.*, 1987; Cohen, Nelson, and Walsh, 2000). Some observers even note that "*the biotechnology industry would not have emerged but for the existence of predictable patents*" (Federal Trade Commission, 2003). Moreover, prior studies show that biotechnology firms with more patents attract more financing and go to IPO faster (Stuart *et al.*, 1999; Baum and Silverman, 2004), while they also achieve higher market valuations once they are publicly traded (Hall *et al.*, 2005 p.32; Sood and Tellis, 2008). Consistent with these observations, numerous studies examining the alliance activity in biotechnology has based measures of innovation performance on counts of patents (*e.g.* Baum, Calabrese, and Silverman, 2000; Owen-Smith and Powell, 2004; Rothaermel and Hess, 2007; Whittington, Owen-Smith, and Powell, 2009).

More traditional accounting-based performance measures, such as return on assets or return on sales, are likely to be less useful as a consistent anchoring point in biotechnology because DBFs tend not to achieve sales or returns until considerable resources have been expended on one or more research and development projects (Pisano, 2006). Therefore, given the loose connection between the technological and product-market productivity in biotechnology, patents appear to be the more relevant performance measure, especially in relation to firms' immediate-term decisions concerning the reconfiguration of their alliance portfolios.

To construct our independent variables, we first calculate historical and social performance aspiration levels of our sample firms for the observation years. Following prior research (Levinthal and March, 1981; Greve, 2003a; Baum *et al.*, 2005; Bromiley and Harris, 2014), we calculate historical aspiration levels based on an exponentially weighted average of historical performance values as follows:

$$Historical\ Aspiration_{it} = (1\text{-}a) * (a * P_{it\text{-}2} + P_{it\text{-}1})$$

where i is a subscript for firms; t is a time subscript; P is the number a focal firm's successful patent applications in year t, and the updating parameter α is the weight attached to the prior performance level P_{t-2} relative to new performance information P_{t-1}. We chose $\alpha = 0.35$ as the value for the updating parameter because this value provided the best fit of the model to our data (Bromiley and Harris, 2014). This relatively low value for α indicates that sampled firms placed a greater weight on new performance information relative to that conveyed by the prior aspiration level. Such a finding is consistent with the idea that more recent performance information may be seen as comparatively more relevant in dynamic settings such as biotechnology. Moreover, given that our sampled firms are all public, it may also reflect the fact that investor pressures lead firms to update their performance aspirations more quickly, by anchoring their aspiration levels in more recent rather than more remote historical performance.

We calculate social aspiration levels based on the average patenting performance of other publicly traded DBFs in a given year (Greve, 2003a; Baum *et al.*, 2005) as follows:

$Social\ aspiration_{it} = (\sum_j P_{jt})/N_t$,

where P_{jt} is the number of patents granted to a publicly traded DBF j in year t, and N_t is the number of other publicly traded DBFs in year t. Our measure restricted social comparison to other publicly traded DBFs, reflecting the idea that compared to private firms, other publicly traded firms are especially relevant to the focal firm as reference points. Moreover, patent grant dates rather than application dates are more suitable from a social comparison perspective, first, because patent applications are not made public until at least 18 months from the original application date, and in a variety of cases they are not made public until patents are granted (USPTO, 2012). Second, information on other firms' patenting should be particularly relevant to, and reliable for, the performance comparison process once patents are known to have been granted.

After we calculate performance aspiration levels, we separately construct two pairs of independent variables (based on historical and social aspiration levels) for below and above aspiration performance by using spline functions to allow performance relative to aspirations to have different effects above and below the aspiration levels (Greve, 2003a).

Performance-Historical aspiration < 0 equals performance minus the aspiration level when performance is below the historical aspiration level, and equals 0 when performance is at or above this level.

Performance-Historical aspiration > 0 equals performance minus the aspiration level when performance is above the historical aspiration level, and equals 0 when performance is at or below the historical aspiration level.

Performance-Social aspiration < 0 equals performance minus the aspiration level when performance is below the social aspiration level, and equals 0 when performance is at or above this level.

Performance-Social aspiration > 0 equals performance minus the aspiration level when performance is above the social aspiration level, and equals 0 when performance is at or below the historical aspiration level.

Our moderator variable, *Alliance portfolio commitment* measures the share of all alliances in a focal firm's existing alliance portfolio that include minority equity investments and/or were joint ventures.

Control variables

We employ a number of control variables at the firm and alliance portfolio level (as of year *t*) that may affect firm's alliance formation decisions. At the firm level, we control for organizational slack as it represents organizational resources available for search via external collaborations and may impact a firm's search behavior (*e.g.* Greve, 2003a). Following prior research, we measure *Absorbed slack* by the ratio of a firm's selling and administrative expenses to the number of its employees, and *Unabsorbed slack* by the ratio of a firm's cash and short term investments to its liabilities (Greve, 2003a). Other firm-level controls include *Firm age*, which captures a focal firm's age in years since incorporation. *Firm profits,* which measures a focal firm's earnings before interest, taxes, depreciation and amortization (EBITDA). *Firm size*, which equals the natural logarithm of a firm's number of employees, and *Firm R&D spending*, which equals the natural logarithm of a firm's R&D expenditure.

At the alliance portfolio level, *Alliance portfolio size* measures the number of alliances in a firm's alliance portfolio. The variable *Technologies in alliance portfolio* captures the share of all 53 technologies listed in the RECAP database that were covered in a firm's alliance portfolio. Two additional variables capture the characteristics of the alliances in a focal firm's alliance portfolio: *Alliances with commercialization component* measures (in percentage points) the share of a firm's alliances that include a commercialization provision for the outcome of the alliance, while *Alliances with R&D component* measures the share of a firm's alliances (in percentage points) that explicitly designate R&D as a major activity in the alliance.

Finally, in addition to firm fixed-effects, all models include fixed effects for the multi-year periods *1985-1987*, *1988-1990*, *1991-1993*, and *1994-1996*, while *1997-2000* is the baseline category. We choose this partitioning of years into multi-year periods because both yearly fixed effects and fixed effects for two-year periods generated considerable multicollinearity, while the estimates on both alternative sets of temporal fixed effects were largely insignificant.

Empirical analysis

All our six dependent variables are nonnegative count variables, we therefore employ a Poisson quasi maximum likelihood estimation with conditional firm fixed effects (Wooldridge, 1999) to empirically test our hypotheses. This method accommodates autocorrelated error terms and overdispersion and is robust to conditional heteroscedasticity. A conditional fixed effects specification generates unbiased and consistent estimates, though it discards firms that only have values of zero on the dependent variable (*e.g.* Hausman, Hall, and Griliches, 1984; Allison and Waterman, 2002)). Therefore, depending on the specific dependent variable, effective sample sizes varied across the models. Nevertheless, to assess the consistency between conditional and unconditional fixed effects estimations, we also estimate all models on the full sample of 1,357 firm-years (200 firms) using OLS fixed effects estimation. This generated virtually identical results across the different hypothesis tests.

RESULTS

Descriptive statistics

Tables 1 presents descriptive statistics and pairwise correlations among our variables. We examined the variance inflation factors (VIFs) of our variables to check whether some moderately high correlations among our explanatory variables may cause a collinearity problem in our regressions. All VIFs are below the commonly accepted threshold of 10, suggesting that our estimations are not affected by multicollinearity among independent variables (Studenmund, 2010).

Our sample reflects the commonly accepted characteristics of biotechnology firms as being relatively young, small, R&D-intensive firms with usually negative returns. The average firm in our sample is 10 years old, has 237 employees and records a loss (before interest, taxes and depreciation) of 150,000 USD while spending approximately 25 million USD for R&D annually, While six firms, formed between 1987 and 1997, entered our dataset two years after formation, the two oldest firms in the sample, Lifecore Biomedical Inc. and Oxis International Inc., both formed in 1965, were founded before the inception of biotechnology as an industry in late 1970s but subsequently focused their main activities in this industry. The largest sample firm measured by the number of employees is Chiron Corp. with 7,434 employees in 1997. Although 167 out of 185 firms in our sample did not generate positive financial earnings during the time period covered by our dataset, the most profitable firm in our sample Amgen Inc. declared earnings of 1.67 billon USD before interest, taxes and depreciation in 1999, while spending 822 million USD for R&D, also the highest in our sample.

Our sample firms also exhibit a high degree of variation in terms of their alliance formation patterns. While the average sample firm has 4.4 alliances in its alliance portfolio, half of which are explicitly formed to conduct R&D, the firm with the largest number of alliances in its alliance portfolio is Affymetrix Inc., with 46 alliances in 2000, 35 of which are specifically formed to conduct R&D. The most common alliance formation behavior in our sample is formation of alliances with novel partners (1.28 per year), followed by alliances in firms' existing technological areas (0.8 per year). Each year in our dataset, the average sample firm forms 0.7 alliances in its existing technological areas with novel partners and 0.02 alliances in novel technological areas with its existing alliance partners. The firm with the greatest number of alliances in existing technologies in any focal year is Affymetrix Inc. which formed 17 such alliances in 1998, 15 of which were with novel partners. Chiron Corp. has the greatest number of alliances in novel technologies in any focal year with 8 such alliances in 1995, all of which are with novel partners. Although on average 17 percent of our sample firms' alliance portfolios consist of equity alliances (alliances with minority equity investments or joint ventures), the alliance portfolios of 20 firms in our sample solely consist of equity alliances. On average seven percent of alliances in our sample firms' alliance portfolios include explicit provisions for commercialization of drug candidates, indicating the nascent stage of biotechnology industry with respect to commercialization of innovation outputs (Pisano, 2006).

Table 1 – Descriptive statistic and pairwise correlations

		Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Alliances in existing technologies	0.783	1.552	0	17	1.000								
(2)	Alliances in novel technologies	0.531	0.963	0	8	0.255	1.000							
(3)	Alliances with existing partners	0.102	0.361	0	3	0.520	0.256	1.000						
(4)	Alliances with novel partners	1.276	1.875	0	17	0.851	0.675	0.382	1.000					
(5)	Alliances in existing technologies with novel partners	0.707	1.400	0	15	0.982	0.246	0.372	0.858	1.000				
(6)	Alliances in novel technologies with existing partners	0.024	0.158	0	2	0.053	0.252	0.420	0.091	0.063	1.000			
(7)	Performance-Historical aspiration > 0	2.509	9.441	0.000	193.962	0.195	0.182	0.289	0.194	0.167	0.231	1.000		
(8)	Performance-Social aspiration > 0	3.409	14.598	0.000	260.574	0.311	0.264	0.351	0.320	0.278	0.210	0.907	1.000	
(9)	Performance-Historical aspiration < 0	-0.979	6.203	-147.530	0.000	-0.241	-0.116	-0.014	-0.255	-0.268	-0.040	0.042	-0.103	1.000
(10)	Performance-Social aspiration < 0	-3.788	3.064	-9.573	0.000	0.127	0.125	0.102	0.138	0.118	0.047	0.274	0.289	-0.065
(11)	Perf.-Hist. asp. < 0 * Alliance portfolio commitment	-0.272	2.301	-58.890	0.000	-0.184	-0.102	0.001	-0.203	-0.205	-0.009	0.031	-0.093	0.909
(12)	Perf.-Social asp. < 0 * Alliance portfolio commitment	-0.551	1.271	-9.573	0.000	0.012	0.029	0.033	0.022	0.008	0.016	0.095	0.101	0.010
(13)	Absorbed slack	73.372	79.317	2.867	1,300.500	-0.062	0.019	-0.053	-0.033	-0.060	-0.040	-0.059	-0.052	0.018
(14)	Unabsorbed slack	5.647	8.604	0.000	136.167	-0.101	-0.099	-0.062	-0.124	-0.100	-0.031	-0.040	-0.065	0.027
(15)	Firm age	10.099	5.066	2	34	0.024	0.064	0.018	0.048	0.022	-0.007	0.018	0.068	-0.072
(16)	Firm profits*	-0.150	92.795	-165.509	1,637.700	0.079	0.191	0.019	0.157	0.082	-0.009	0.101	0.213	-0.095
(17)	Firm size	237.207	625.183	1	7,434	0.373	0.346	0.211	0.438	0.378	0.168	0.385	0.576	-0.403
(18)	Firm R&D spending*	24.815	62.432	0.000	822.800	0.321	0.335	0.180	0.395	0.318	0.077	0.346	0.550	-0.280
(19)	Alliance portfolio size	4.366	5.224	0	46	0.679	0.326	0.462	0.631	0.652	0.160	0.306	0.453	-0.236
(20)	Technologies in alliance portfolio (%)	0.056	0.060	0.000	0.491	0.565	0.372	0.349	0.571	0.553	0.158	0.347	0.492	-0.239
(21)	Alliances with commercialization component (%)	0.074	0.171	0.000	1.000	0.029	0.038	0.016	0.038	0.029	0.010	0.028	0.033	-0.035
(22)	Alliance portfolio commitment	0.165	0.250	0.000	1.000	0.053	0.071	0.038	0.071	0.050	0.019	0.063	0.067	-0.071
(23)	Alliances in the portfolio with R&D component (%)	0.490	0.392	0.000	1.000	0.217	0.147	0.153	0.228	0.210	0.068	0.093	0.105	-0.041

All correlations above 0.06 are significant at 0.05 level

*In 1,000,000 USD

Table 1 – Descriptive statistics and pairwise correlations (continued)

		(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
(10)	Performance-Social aspiration < 0	1.000													
(11)	Perf.-Hist. asp. < 0 * Alliance portfolio commitment	-0.059	1.000												
(12)	Perf.-Social asp. < 0 * Alliance portfolio commitment	0.385	0.079	1.000											
(13)	Absorbed slack	-0.238	0.016	-0.074	1.000										
(14)	Unabsorbed slack	0.027	0.018	0.010	0.005	1.000									
(15)	Firm age	-0.089	-0.069	0.062	0.052	-0.156	1.000								
(16)	Firm profits	0.111	-0.075	0.049	0.037	-0.046	0.157	1.000							
(17)	Firm size	0.241	-0.323	0.089	-0.043	-0.125	0.198	0.672	1.000						
(18)	Firm R&D spending	0.258	-0.267	0.068	-0.015	-0.108	0.177	0.739	0.850	1.000					
(19)	Alliance portfolio size	0.180	-0.189	0.033	-0.080	-0.139	0.084	0.207	0.557	0.490	1.000				
(20)	Technologies in alliance portfolio (%)	0.217	-0.190	-0.022	-0.107	-0.146	0.081	0.320	0.636	0.592	0.832	1.000			
(21)	Alliances with commercialization component (%)	0.074	-0.096	-0.297	-0.068	-0.006	-0.018	-0.007	0.041	0.059	0.065	0.110	1.000		
(22)	Alliance portfolio commitment	0.096	-0.167	-0.652	-0.066	-0.012	-0.113	0.012	0.053	0.095	0.058	0.162	0.442	1.000	
(23)	Alliances in the portfolio with R&D component (%)	0.157	-0.067	-0.265	-0.183	0.044	-0.148	0.034	0.091	0.103	0.293	0.354	0.339	0.444	1.000

All correlations above 0.06 are significant at 0.05 level/

*In 1,000,000 USD

In Tables 2 and 3 we separately present the results of alliance portfolio technological scope and partner mix analyses, respectively. Table 4 estimates the models with the same independent variables but with simultaneous reconfiguration of technological scope and partner choice as dependent variables, with which we test our hypotheses. Note that the independent variables measuring below-aspiration performance are constructed such that they take greater negative values as performance decreases further below aspirations. Therefore, negative coefficients of *Performance-Historical aspiration* < 0 and *Performance-Social aspiration* < 0 variables imply a positive effect on the dependent variables.

Alliance portfolio technological scope

In Table 2, Model 1 shows that firms' alliance formations in their existing technological areas increase as their innovation performance falls below their historical aspiration levels, and decrease when their performance exceeds these levels. Model 2 shows that while performance above social aspiration levels has a negative effect on alliance formations in existing technologies, performance below social aspirations does not have any effect. Together, these results are in line with H1. While Model 3 shows that performance relative to historical aspiration levels has no significant effect on alliance activity in novel technological areas, Model 4 shows that performance above social aspirations is conducive to formation of alliances in novel technologies, consistent with H3.

Table 2 – Fixed-effects models of alliance portfolio technological scope

	Alliances in existing technologies		Alliances in novel technologies	
	1	2	3	4
Absorbed slack	0.001	0.001	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Unabsorbed slack	-0.020**	-0.021*	-0.031***	-0.033***
	(0.010)	(0.011)	(0.012)	(0.012)
Firm age	0.073*	0.056	-0.003	-0.010
	(0.039)	(0.042)	(0.060)	(0.062)
Firm profits	-0.001***	-0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size	0.147	0.228	0.162	0.153
	(0.142)	(0.143)	(0.240)	(0.238)
Firm R&D spending	0.037	0.016	0.189	0.194
	(0.090)	(0.096)	(0.177)	(0.178)
Alliance portfolio size	-0.031***	-0.031***	-0.013	-0.013
	(0.009)	(0.010)	(0.032)	(0.032)
Technologies in alliance portfolio	6.369***	6.562***	-5.487**	-6.219**
	(1.435)	(1.380)	(2.771)	(2.833)
Alliances with commercialization component	-0.266	-0.382	-0.223	-0.207
	(0.428)	(0.442)	(0.450)	(0.443)
Alliance portfolio commitment	-0.656**	-0.564**	0.029	0.004
	(0.282)	(0.279)	(0.375)	(0.367)
Alliances in the portfolio with R&D component	0.977***	0.983***	-0.393	-0.376
	(0.323)	(0.332)	(0.303)	(0.297)
Performance-Historical aspiration > 0	-0.002*		0.004	
	(0.001)		(0.003)	
Performance-Social aspiration > 0		-0.003***		0.006**
		(0.001)		(0.003)
Performance-Historical aspiration < 0	-0.005*		-0.001	
	(0.002)		(0.002)	
Performance-Social aspiration < 0		0.013		0.003
		(0.028)		(0.027)
Observations	792	792	937	937
Log-likelihood	-682.3	-683.8	-652.1	-650.1
Prob > chi2	0.000	0.000	0.000	0.000

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All models include year dummies. All significance tests are two-tailed.

Alliance portfolio partner mix

In Table 3, Models 1 and 2 show that above-aspiration performance relative to both historical and social reference points positively influences the formation of new alliances with existing alliance partners, consistent with H3. Models 3 and 4 test the effects of performance relatable to aspirations on alliance activities with novel partners, and show that performance below historical (but not social) aspirations lead to formation of new alliances with novel partners, in line with H1. Models 5 and 6 add the interaction of below-aspiration performance with alliance portfolio commitment. Model 5 shows that although firms performing below their historical aspirations increase their propensity to form new alliances with novel partners, this propensity is curtailed by their equity commitments to their existing alliance partners. This result is in line with H2. Like Model 4, Model 6 reports no significant effect of performance relative to social aspirations on alliance formations with novel partners.

Alliance portfolio technological scope and partner mix

In Table 4 Models 1 through 6 report the results of analyses of simultaneous change in alliance portfolio technological scope and partner mix. Although the results provided by the previous analyses that separately examine changes in technological scope and partner choice are consistent with our predictions, these models with dependent variables that simultaneously capture both dimensions of alliance portfolio reconfiguration allow for a more rigorous testing of our hypotheses.

Models 1 and 2 show that above-aspiration performance relative to both historical and social reference points is conducive to alliance formation in novel technological areas with existing alliance partners, providing strong support to H3. Figure 1 illustrates these relationships.

Table 3 – Fixed-effects models of alliance portfolio partner mix

	Alliances with existing partners		Alliances with novel partners			
	1	2	3	4	5	6
Absorbed slack	0.002	0.002	0.002***	0.002***	0.002***	0.002***
	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Unabsorbed slack	-0.055**	-0.054**	-0.021***	-0.021***	-0.021***	-0.021***
	(0.027)	(0.027)	(0.007)	(0.007)	(0.007)	(0.007)
Firm age	0.078	0.098	0.037	0.021	0.038	0.021
	(0.117)	(0.112)	(0.031)	(0.035)	(0.031)	(0.034)
Firm profits	-0.002**	-0.002**	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Firm size	-0.004	-0.100	0.175*	0.205*	0.154	0.205*
	(0.325)	(0.322)	(0.104)	(0.120)	(0.105)	(0.119)
Firm R&D spending	0.425*	0.448*	0.060	0.051	0.070	0.051
	(0.253)	(0.251)	(0.079)	(0.085)	(0.079)	(0.085)
Alliance portfolio size	0.001	-0.000	-0.030***	-0.029***	-0.030***	-0.029***
	(0.019)	(0.020)	(0.008)	(0.008)	(0.008)	(0.009)
Technologies in alliance portfolio	1.736	1.332	2.006*	2.144**	1.861*	2.163**
	(2.492)	(2.668)	(1.026)	(1.091)	(1.049)	(1.092)
Alliances with commercialization component	-0.618	-0.455	-0.300	-0.350	-0.324	-0.344
	(0.846)	(0.853)	(0.292)	(0.296)	(0.300)	(0.296)
Alliance portfolio commitment	-1.244*	-1.398**	-0.133	-0.089	-0.105	-0.044
	(0.700)	(0.695)	(0.213)	(0.215)	(0.217)	(0.273)
Alliances in the portfolio with R&D component	2.103**	2.098**	0.079	0.070	0.079	0.070
	(0.821)	(0.835)	(0.211)	(0.209)	(0.211)	(0.208)
Performance-Historical aspiration > 0	0.006***		-0.002		-0.002	
	(0.002)		(0.001)		(0.001)	
Performance-Social aspiration > 0		0.007***		-0.002		-0.002
		(0.002)		(0.001)		(0.001)
Performance-Historical aspiration < 0	0.012		-0.004**		-0.010***	
	(0.008)		(0.002)		(0.003)	
Performance-Social aspiration < 0		-0.020		-0.000		-0.003
		(0.056)		(0.017)		(0.022)
Perf.-Hist. asp. < 0 × Alliance portfolio commitment					0.020**	
					(0.010)	
Perf.-Social asp. < 0 × Alliance portfolio commitment						0.016
						(0.071)
Observations	422	422	988	988	988	988
Log-likelihood	-152.8	-152.9	-1010	-1012	-1009	-1012
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000

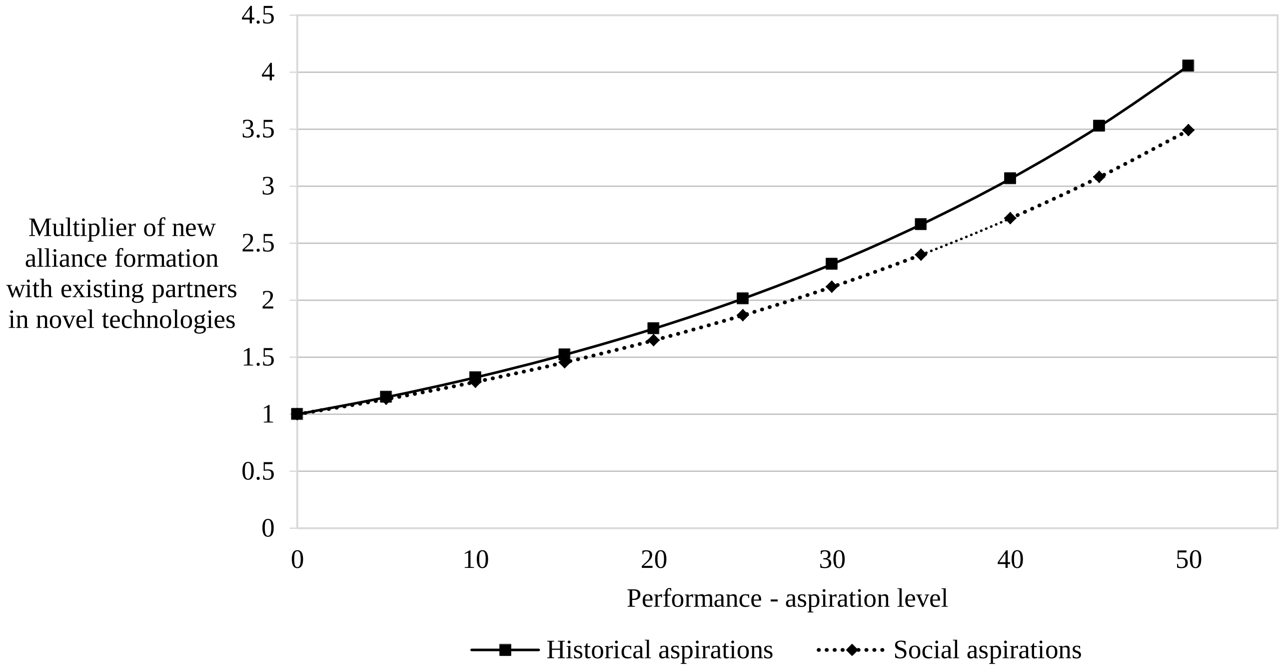
*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All models include year dummies. All significance tests are two-tailed.

Table 4 – Fixed-effects models of alliance portfolio technological scope and partner mix

	Alliances in novel technologies with existing partners		Alliances in existing technologies with novel partners			
	1	2	3	4	5	6
Absorbed slack	-0.013**	-0.015**	0.001	0.001	0.001	0.001
	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
Unabsorbed slack	-0.109*	-0.121**	-0.020**	-0.020**	-0.020**	-0.020**
	(0.057)	(0.061)	(0.010)	(0.010)	(0.010)	(0.010)
Firm age	-0.174	-0.140	0.056	0.036	0.059	0.032
	(0.273)	(0.273)	(0.042)	(0.046)	(0.042)	(0.046)
Firm profits	0.002	0.002	-0.001***	-0.001***	-0.001***	-0.001***
	(0.007)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)
Firm size	-1.279*	-1.394**	0.154	0.256	0.103	0.275*
	(0.693)	(0.671)	(0.153)	(0.159)	(0.158)	(0.160)
Firm R&D spending	0.762**	0.788**	0.012	-0.013	0.035	-0.025
	(0.339)	(0.356)	(0.101)	(0.108)	(0.103)	(0.109)
Alliance portfolio size	0.211**	0.225***	-0.034***	-0.034***	-0.032***	-0.033***
	(0.097)	(0.086)	(0.010)	(0.011)	(0.010)	(0.011)
Technologies in alliance portfolio	-18.750**	-21.926***	6.558***	6.873***	6.333***	6.778***
	(7.535)	(7.905)	(1.369)	(1.317)	(1.416)	(1.319)
Alliances with commercialization component	-0.088	-0.286	-0.218	-0.358	-0.277	-0.419
	(2.647)	(2.565)	(0.441)	(0.467)	(0.452)	(0.459)
Alliance portfolio commitment	0.894	1.161	-0.589**	-0.474*	-0.538*	-0.857**
	(1.684)	(1.476)	(0.288)	(0.280)	(0.294)	(0.369)
Alliances in the portfolio with R&D component	0.331	0.710	0.852***	0.854**	0.846**	0.864**
	(1.271)	(1.412)	(0.330)	(0.338)	(0.332)	(0.340)
Performance-Historical aspiration > 0	0.028***		-0.003**		-0.002*	
	(0.005)		(0.001)		(0.001)	
Performance-Social aspiration > 0		0.025***		-0.004***		-0.004***
		(0.006)		(0.001)		(0.001)
Performance-Historical aspiration < 0	-0.013		-0.005**		-0.016***	
	(0.010)		(0.002)		(0.003)	
Performance-Social aspiration < 0		0.166		0.013		0.037
		(0.148)		(0.029)		(0.034)
Perf.-Hist. asp. < 0 * Alliance portfolio commitment					0.033***	
					(0.010)	
Perf.-Social asp. < 0 * Alliance portfolio commitment						-0.142
						(0.102)
Observations	189	189	792	792	792	792
Log-likelihood	-38.68	-37.99	-653.6	-655.2	-652.4	-653.8
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All models include year dummies. All significance tests are two-tailed.

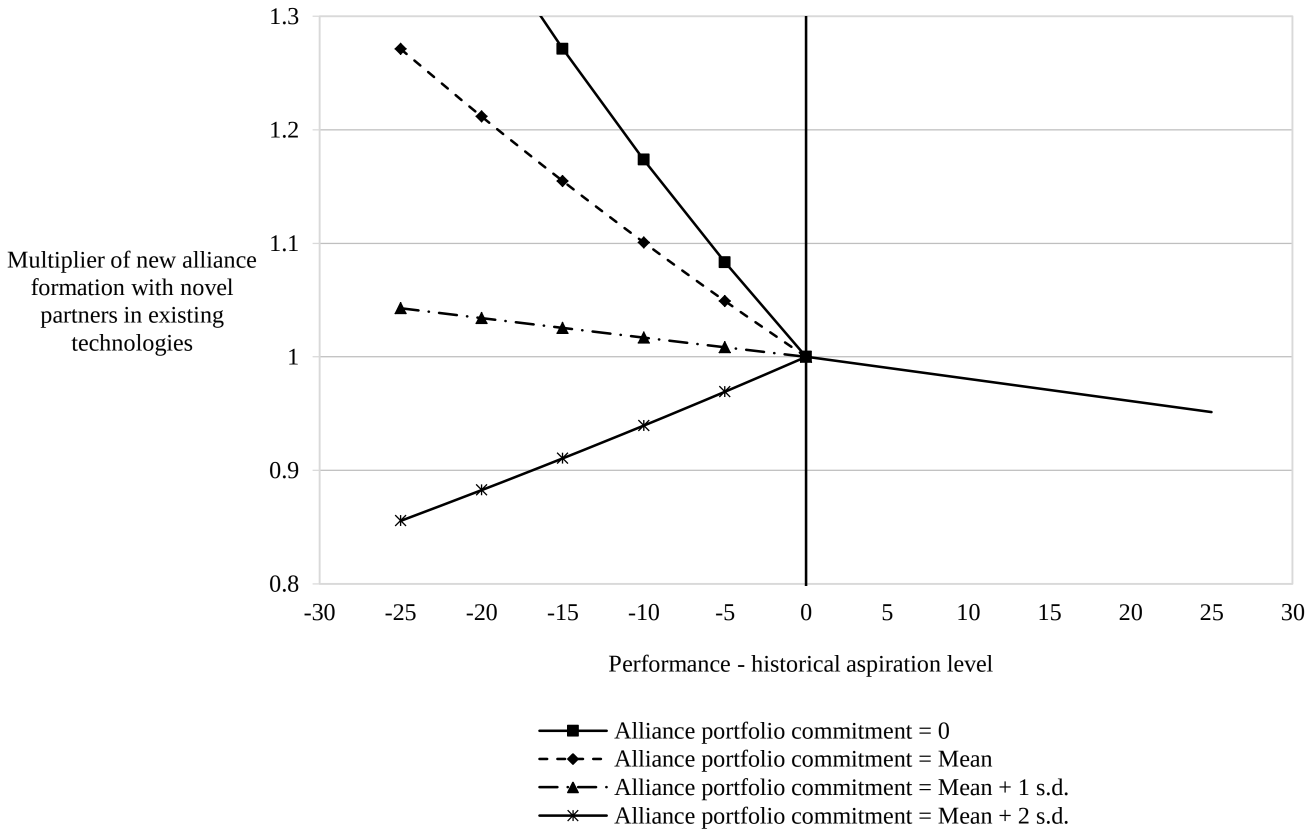
Figure 1 – Above-aspiration performance and new alliance formation



Models 3 and 4 show that while performance below historical (but not social) aspiration levels positively influences alliance formation with novel partners in existing technological areas, as predicted by H1, the impact of above-aspiration performance relative to both historical and social reference points on this type of alliance activity is negative. Overall, our analyses provide support to H1.

Model 5 tests the impact of alliance portfolio commitment on formation of alliances with novel partners in existing technological areas as a response to performance below historical aspirations. The estimates show a negative impact of equity commitments to existing alliance partners on this type of alliance activity. This finding confirms and refines our previous analysis (Table 3 Model 5), and provides support to H2. Figure 2 illustrates the curtailing impact of alliance portfolio commitment on the propensity of new alliance formation with novel partners in existing technologies. Model 6 reports no significant impact of performance relative to social aspirations on alliance formations with novel partners in existing technologies.

Figure 2 – Interaction between performance below historical aspirations and alliance protfolio commitment



Overall, our analyses of changes in alliance portfolio technological scope and partner mix, examined separately as well as simultaneously, support our hypotheses. While we generally find that above-aspiration performance relative to historical and social aspiration levels have similar effects on alliance portfolio decisions, we find no significant effect of performance below social aspirations. This suggests that while firms assess their failures by internal criteria, they evaluate their successes by internal as well as external standards. Research in this area suggests that when managers view their firms as comparable to others, they tend to evaluate their performance by external standards, but they prefer internal criteria when they view their firms as different than others (Greve, 2003b; Audia and Greve, 2006). In our empirical context, the biotechnology industry, both viewpoints can be justified. On the one hand, all biotechnology firms are similar in that they pursue drug R&D with unconventional methods using a limited set of business strategies (Pisano, 2006). On the other hand, each drug R&D project is unique and shares little common ground for problem-solving with others. It is therefore likely that while biotechnology firms may consider obtaining more patents than other biotechnology firms as an indication for success (as it is an intuitive and easily quantifiable performance indication), they may not be evaluating obtaining fewer patents than others as a failure, as long as they meet their internal performance criteria.

DISCUSSION

In this study we examine how firms reconfigure their alliance portfolios as a result of their innovation performance relative to aspirations, and find that below-aspiration performance motivates firms to form new alliances in their existing technological areas yet with novel partners, whereas above-aspiration performance leads them to form new alliances in novel technological areas with their existing alliance partners. We further find that equity commitments to existing alliance partners reduces firms' propensity to form new alliances in existing technological areas with novel partners. Before proceeding to theoretical and managerial implications of our findings, we would like to elaborate on our application of performance feedback theory, which is traditionally associated with accounting measures of performance, in the context of innovation performance and its possible consequences for the generalizability of our results.

Performance feedback theory is based on the behavioral theory of the firm (Cyert and March, 1963) which argues that "*managers compare expected firm performance to aspiration levels that depend on prior aspirations, prior performance, and the performance of comparable firms*." (Bromiley and Harris, 2014 p.338). Researches using performance feedback theory to explain various organizational decisions (*e.g.* Greve, 2003a; Audia and Greve, 2006), mostly relied on accounting-based performance indicators such as return on assets, return on equity, and return on sales to measure firm performance relative to aspirations. Accounting-based performance measures are well-suited to empirically test predictions based on performance feedback theory because firms are mostly evaluated by shareholders, creditors and other stakeholders based on such performance measures. Applying performance feedback theory to the context of innovation performance relies on the assumption that managers compare their actual innovation output with prior periods as well as with the innovation output of comparable firms, and modify their search behaviors based on these comparisons. While the impact of innovation performance on firms' search behaviors is not as strongly established in prior research as that of accounting performance, we believe that in our empirical context (the biotechnology industry) innovation performance is more likely to influence firm behavior than accounting-based performance measures because the overwhelming majority of biotechnology firms have never generated financial profits, and innovation performance is the most important performance metric by which our sample firms are evaluated. (Pisano, 2006 p.118)

While there are a few profitable biotechnology firms such as Amgen and Genentech, the majority of firms in the industry have yet to translate their scientific accomplishments in drug development into financial returns. Because of the high degree of uncertainty and long-lead times in drug R&D, biotechnology is a unique industry in which the majority of firms can be expected to sustain prolonged periods of financial losses (Pisano, 2006 p.118). Despite the lack of prospects for short-term financial gains, biotechnology firms are considered as viable investments by a wide range of investors, and as attractive alliance partners by large pharmaceutical firms, because of high potential returns when their innovative efforts will lead to commercially viable drugs. Due to high capital requirements of drug R&D and the need to access complementary assets via alliances, maintaining the interest of investors and potential alliance partners is of vital importance for biotechnology firms. Hence, these firms need to convince potential investors and alliance partners that they have the necessary R&D capabilities to convert financial resources (investments) to drugs (Pisano, 2006 p.118) by exhibiting an adequate level of innovation performance. We therefore suggest that biotechnology firms would continuously adjust their strategies, including their search behaviors, so as to maintain an adequate level of innovation performance, since this is the most feasible way for these firms to sustain their viability as economic entities in the absence of financial profits in the short-run. While the connection between innovation performance and search behaviors may be weaker in more established industries in which counting performance measures better reflect long-term profitability, we believe that our conceptual framework and empirical findings are relevant to emerging, high-technology industries in which firms' economic viability depends on successful commercialization of scientific breakthroughs.

Contributions to the literature

We make several contributions to the literature. First, we complement the scarce body of research on alliance portfolio evolution by providing rare empirical evidence on the antecedents of firms` alliance portfolio expansion decisions (Parise and Casher, 2003; Hoffmann, 2007; Wassmer, 2010; Wassmer and Dussauge, 2012; Lahiri and Narayanan, 2013). Existing research in this area largely focuses on how firms can improve their competitive position by using their alliance portfolios as a strategic tool, implicitly assuming that firms make alliance formation decisions rationally to enhance the alignment between their alliance portfolios and their strategic objectives. Our results underscore the behavioral aspect of alliance formation decisions by showing that managers make such decisions not only based on long-term strategic goals but also as a response to short-term stimuli such as performance feedback. Our results thus help explain why in many cases alliance portfolios evolve to a "random" collection of individual alliances rather than to purposefully designed strategic tools (Bamford and Ernst, 2002; Kale and Singh, 2009).

Second, our results refine the relationship between problemistic and slack-driven search as a result of performance relative to aspirations on the one hand, and risk-taking on the other. A large body of literature suggest that both problemistic and slack-driven search are increasingly associated with risk-taking as performance diverges from aspiration levels (*e.g.* Cyert and March, 1963; Greve, 2003a; Baum *et al.*, 2005). Although the difference between the drivers of problemistic and slack-driven search (addressing an existing problem for the former and experimentation with resources for the latter) point at a possible difference between the domains in which problemistic and slack-driven search take place, these studies do not make a distinction between the type and nature of risk-taking associated with these search behaviors. Specifically, while problemistic search is more likely to focus on the existing area of expertise of a firm, slack-driven search allows a firm to expand its area of expertise. Our findings confirms this distinction and suggest that firms performing below aspirations remain within the technological scope of their alliance portfolios and alter their resource configurations (by allying with new partners) to address performance problems whereas firms performing above aspirations keep their alliance partners and expand the technological scope of their alliance portfolios. In other words, firms in the failure range change their "toolbox" to improve their performance, firms in the success range use their existing "toolbox" for their exploration activities in novel areas.

Our results support the view that managers' alliance formation decisions are prone to cognitive biases (Cannon, 2005; Edmondson, 2011). Our analysis suggests that managers attribute poor performance to their alliance partners and believe that performance would improve if they ally with "better" partners". Similarly, above-aspiration performance implicitly confirms managers' choices of alliance partners. In addition, our results suggest that problemistic search requires a shorter time-frame to obtain positive results than slack-driven search (Greve, 2003a). Lehman *et al.* (2011) find that as the time between a decision and the realization of its consequences decreases, decision makers' expectations of quicker results from their actions increases. While firms engaged in problemistic search aim to obtain performance improvements by the next performance feedback point (one year in our study), firms engaged in slack-drive search can afford longer trajectories for their exploration activities as they do not face an imminent threat of failure. When exploration in new technological areas is time-consuming and highly uncertain, as is the case in many high-technology industries such as biotechnology (Pisano, 2006), managers of firms in the failure range might consider an alliance with a novel partner that might provide new solutions to their existing problems as a more feasible short-term solution (Beckman *et al.*, 2004; Li *et al.*, 2008). Conversely, managers of firms in the success range, unconstrained by imminent deadlines, might prefer to capitalize on their relationship-specific assets with their current alliance partners (*e.g.* Gulati, 1995; Beckman *et al.*, 2004; Baum *et al.*, 2005) to engage in exploration activities.

Previous studies show that inertia (Hannan and Freeman, 1977) resulting from embeddedness in existing partnership networks reduces uncertainty associated with known alliance partners, and that past investments in relationship-specific assets makes firms insensitive to potentially beneficial cooperation opportunities with novel alliance partners (Li and Rowley, 2002; Duysters and Lemmens, 2003; Hagedoorn and Frankort, 2008). Our findings confirm and refine the relationship between inertia and alliance partner selection. On the one hand, in the presence of negative performance feedback, firms increase their propensity to ally with novel partners despite the costs and risks of doing so. Our findings thus show that performance feedback is a powerful factor that helps firms overcome inertial forces in favor of change. On the other hand, equity commitments to existing alliance partners weaken this relationship, suggesting that contractual inertial forces are more powerful than social pressures. A fruitful direction for future research is to investigate the performance implications of the role of inertia in restricting firms' ability to respond to negative performance feedback by means of alliances with novel partners.

Our findings also have implications for research on alliance portfolio diversity. While numerous studies examine the impact of different dimensions of alliance portfolio diversity on firm performance (*e.g.* Baum *et al.*, 2000; Lavie, 2007; Jiang *et al.*, 2010; Duysters *et al.*, 2012; Van de Vrande, 2013), the understanding of the antecedents of such diversity remains limited. Our findings suggest that below-aspiration performance increases the diversity of alliance partners within alliance portfolios whereas above-aspiration performance increases technological diversity. As new alliances that are formed as a result of performance feedback might not always align with the role of alliance portfolios as strategic tools, a fruitful direction for future research can be to examine whether the drivers of alliance portfolio diversity (strategic positioning or performance feedback) influence the established relationships between alliance portfolio diversity and firm performance.

Managerial implications

Our results, combined with prior research on alliance portfolios, underscore the need that managers should be self-reflective in their alliance decisions. Specifically, managers should consider the portfolio-level consequences of forming new alliances with novel partners (thus increasing the partner diversity of their alliance portfolios), or in novel technological areas (thus increasing their portfolio's technological diversity) to address short-term performance problems. While partner diversity within alliance portfolios can potentially improve the overall value of the portfolio to a firm, it also places a substantial burden on the firm's alliance management capability (Sarkar, Aulakh, and Madhok, 2009; Duysters *et al.*, 2012). Therefore, when a firm lacks a well-developed alliance management capability, the addition of a new alliance with a novel partner to the portfolio as a consequence of poor performance can decrease the value that a firm can extract not only from that alliance but also from its already existing alliances. Similarly, increasing technological diversity within an alliance portfolio can decrease performance outcomes of exploration activities in distant technological areas (Vasudeva and Anand, 2011), suggesting that performance outcomes from slack-driven search by means of a new alliance depend on the existing technological diversity within a firm's alliance portfolio.

CHAPTER 3

KNOWLEDGE ACQUISITION OR COMPLEMENTARY SPECIALIZATION? ANTECEDENTS OF ALTERNATIVE KNOWLEDGE UTILIZATION OUTCOMES IN ALLIANCES

ABSTRACT

Research about external knowledge utilization through alliances suggests that firms can more successfully utilize their alliance partners' knowledge when their technological capabilities overlap with those of their partners and when they have prior experience in alliances. This research however largely focuses on knowledge acquisition from alliance partners as the main knowledge utilization strategy in alliances, ignoring alternative strategies such as complementary specialization, which allows alliance partners to specialize in complementary areas without seeking to acquire each other's knowledge. In this paper we compare the impact of technological overlap and alliance experience on these two knowledge utilization strategies. We argue that technological overlap enhances firms' knowledge recognition skills and is conducive to complementary specialization within an alliance, whereas alliance experience improves knowledge assimilation skills and is conducive to inter-partner knowledge acquisition. Our empirical analysis on a multi-industry sample of 971 alliances supports our predictions.

Keywords: Alliances, knowledge utilization, learning, complementary specialization, absorptive capacity

INTRODUCTION

The surge in the rate of technological innovation in the last three decades has motivated many firms to increase their use of strategic alliances to augment and upgrade their technological capabilities (Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012). In view of these developments, researchers have extensively studied how firms can benefit from technological capabilities of their alliance partners. While acquiring knowledge from alliance partners is emphasized as the key benefit to partnering firms of alliances, (Hamel, 1991; Inkpen, 1998; Dussauge *et al.*, 2000; Inkpen and Tsang, 2007), alliances also allow partnering firms to jointly apply their complementary knowledge bases toward a commercial outcome by specializing in their distinct but related areas. (Nakamura *et al.*, 1996; Lubatkin *et al.*, 2001; Mowery *et al.*, 2002; Grant and Baden-Fuller, 2004). The goal of these alliances is complementary specialization (CS), rather than knowledge acquisition (KA) (Nakamura *et al.*, 1996; Mowery *et al.*, 2002; Inkpen and Tsang, 2007), because each alliance partner focuses on its own area of expertise. Although they are less common than KA alliances, CS alliances play an important role in the development and commercialization of large-scale, technology-driven projects. Prominent examples include the alliance between Daimler and SMH (the producer of Swatch watches) to design and produce the Smart car, as well as the Airbus consortium, whose members specialize in the design and production of specific parts of Airbus aircrafts.

Although CS alliances form an efficient strategy for innovation and are frequently used in many high-technology settings, such as aircraft engineering (Mowery *et al.*, 2002; Inkpen and Tsang, 2007), the automotive industry (Grant and Baden-Fuller, 2004), information technology (Lubatkin *et al.*, 2001), and biotechnology (Al-Laham, Amburgey, and Baden-Fuller, 2010), very little is known about the specific processes and mechanisms at work in such alliances. Besides this managerial relevance, increasing our understanding of CS alliances is of key importance given the impact of new knowledge creation (Jiang and Li, 2009) and cost-benefit trade-offs (Duso, Pennings, and Seldeslachts, 2009) on the innovation outcomes and sustainability of alliances. Unlike KA alliances, which facilitate the transfer of existing knowledge between alliances partners and frequently initiate "learning races" between them (Khanna *et al.*, 1998), CS alliances facilitate the creation of new knowledge and promote cooperative rather than competitive behavior, increasing the efficiency and sustainability of collaboration.

Over the past several years, academic alliance research has focused largely on KA in alliances, thereby ignoring the role of other important knowledge utilization strategies, such as CS, in facilitating innovation outcomes. In the only empirical study investigating the antecedents of CS in alliances, Mowery, Oxley, and Silverman (2002) demonstrate that technological overlap between alliance partners enhances both KA and CS in alliances. Although the authors present an interesting finding that technological overlap, traditionally associated with KA (*e.g.* Cohen and Levinthal, 1990; Mowery *et al.*, 1996; Lane and Lubatkin, 1998; Schildt, Keil, and Maula, 2012), is also conducive to CS, the empirical limitations of their study prevent a thorough understanding of the mechanisms that connect the antecedents ıf external knowledge utilization to its outcomes in the form of KA or CS.

This paper seeks to provide a more thorough analysis of the factors that are likely to influence KA and CS in alliances by extending the study of Mowery, Oxley, and Silverman (2002) in two important ways. First, we focus on multiple antecedents of knowledge utilization that affect different sets of capabilities enabling firms to utilize external knowledge. In addition to technological overlap, which enhances firms' recognition and evaluation of their alliance partners' capabilities (Mowery *et al.*, 1996; Dyer and Singh, 1998; Lane and Lubatkin, 1998;

Mowery *et al.*, 2002), we analyze the role of alliance experience as a determinant of firms' external knowledge utilization capabilities, since such experience improves firms' abilities to acquire know-how from external sources (Sampson, 2005; Heimeriks and Duysters, 2007). Second, rather than using the divergence of technological capabilities of alliance partners as a proxy for CS, as has been done in previous work (Mowery *et al.*, 2002), we employ a new measure that takes both the relative distance and the technological complementarity between alliance partners' capabilities into account. Our analyses of 971 alliances suggest that technological overlap is more conducive to CS than to KA, while alliance experience has a stronger relationship to KA than to CS. Given the limited empirical evidence on CS in alliances (Mowery *et al.*, 1996; Lubatkin *et al.*, 2001; Mowery *et al.*, 2002; Grant and Baden-Fuller, 2004; Inkpen and Tsang, 2007), we contribute to the existing literature by exploring how such factors that are recognized to influence external knowledge utilization impact CS, in comparison to KA, in alliances. Our findings also provide guidance to managers in terms of their policy decisions regarding the utilization of external knowledge.

This paper proceeds as follows. After we briefly review the literature on learning and knowledge utilization in alliances, we develop hypotheses to be tested. We then describe our data and methods. The empirical results are presented in the section after that. We conclude with a discussion of the results and their implications.

THEORY AND HYPOTHESES

Knowledge utilization in alliances: Prior research

Spurred by a realization of the increasing importance, from the early 1980s on, of strategic alliances as sources of external knowledge, management researchers began investigating how firms benefit from collaborating with other firms. Early research in this area suggests that firms can improve their competitiveness by collaborating with competitors for the purpose of acquiring skills and capabilities underlying their competitive advantages (Hamel *et al.*, 1989; Hamel, 1991). The idea of enhancing competitiveness by transferring knowledge from alliance partners is not surprising since alliances provide partnering firms with access to one another's capabilities (Inkpen, 1998; Kale, Dyer, and Singh, 2002) and coordination and cooperation mechanisms that enable knowledge transfer (Mowery *et al.*, 1996; Inkpen and Tsang, 2007). Consequently, researchers focused their attention on identifying the factors that influence knowledge acquisition from alliance partners (*e.g.* Khanna *et al.*, 1998; Larsson *et al.*, 1998; Dussauge *et al.*, 2000; Inkpen and Tsang, 2007).

The coordination and collaboration mechanisms provided by alliances also allow firms to pool their complementary capabilities and work together toward a joint commercial outcome, thereby sharing the costs and reducing the risks of innovation (Inkpen and Tsang, 2007). These alliances allow partnering firms to more specifically target their innovative efforts by specializing in their respective areas of expertise, rather than trying to internally replicate each other's knowledge, which leads to CS within the alliance (Nakamura *et al.*, 1996; Mowery *et al.*, 2002). CS increases the efficiency of innovation because it allows firms to access and utilize new capabilities without being exposed to the costs and uncertainties associated with their acquisition (Grant and Baden-Fuller, 2004).

Researchers have used various theoretical perspectives to study knowledge utilization in alliances, such as the absorptive capacity approach (Mowery *et al.*, 1996, 2002), the exploration and exploitation framework (*e.g.* Rothaermel, 2001; Rothaermel and Deeds, 2004; Colombo, Grilli, and Piva, 2006; Lavie and Rosenkopf, 2006), transaction cost theory (Nakamura *et al.*, 1996; Hennart and Zeng, 2005), and organizational learning (*e.g.* Hamel *et al.*, 1989; Powell, Koput, and Smith-Doerr, 1996; Inkpen and Tsang, 2007). While some of these studies recognize CS as a viable knowledge utilization strategy, they generally focus on KA as the main (and often sole) benefit of alliances to partnering firms. Because of the differences in terms of strategic goals and knowledge exchange processes between KA and CS alliances (Lubatkin *et al.*, 2001; Mowery *et al.*, 2002; Grant and Baden-Fuller, 2004; Lui, 2009), the findings regarding the inducements and obstacles to KA in alliances have limited applicability to CS. As a result, the theoretical insights and empirical evidence regarding the antecedents of CS remain rather scant. With the exception of Mowery, Oxley, and Silverman (2002), who showed that technological overlap, as measured by reciprocal patent citations among alliance partners, enhances both KA and CS in alliances, no scholar, to our knowledge, has empirically compared the antecedents of KA and CS, which leaves this area of study open for potential contribution.

Technological overlap and knowledge utilization

Technological overlap between two or more firms exists when these firms have overlapping technological knowledge bases *i.e.* sets of knowledge that they demonstrated familiarity with, or mastery of (Ahuja and Katila, 2001 p.201). Within an alliance, technological overlap enhances partnering firms` understanding of the meaning and value of each other's technological knowledge bases, and provides them with "absorptive capacity" to recognize and ultimately assimilate each other's knowledge (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998). While the absorptive capacity argument suggests that technological overlap leads to KA in alliances, it can also allow alliance partners to access and benefit from each other's knowledge without assimilating it by facilitating the development of mechanisms for combining their knowledge bases, thus making CS a viable knowledge utilization outcome within the alliance.

The literature provides empirical evidence that supports both viewpoints. While Mowery, Oxley and Silverman (1996, 1998, 2002) find a significant and positive relationship between alliance partners` technological overlap before and after alliance formation, suggesting that pre-alliance technological overlap leads to inter-partner knowledge transfers, hence KA, during the course of the alliance, they also show that technological overlap is also conducive to CS (Mowery *et al.*, 2002). Below we compare the role of technological overlap in alternative knowledge utilization strategies, KA and CS, in alliances.

Because new knowledge needs to be understood before it can be utilized, an accurate understanding and evaluation of alliance partners' knowledge is essential for KA, as well as for CS. Therefore, technological overlap enhances both of these knowledge utilization strategies (Mowery *et al.*, 2002). For KA, however, evaluation of partner knowledge needs to be followed by its assimilation, which requires internalizing the know-how associated with that knowledge. As suggested by the early literature on knowledge utilization, merely knowing *about* external knowledge does not automatically give a firm the ability to internally replicate and use it: the firm also needs to know *how* to use the external knowledge, an understanding it can gain by participating in the application of that knowledge (for a discussion see Brown and Duguid, 2001 p.203-204). In line with these arguments, absorptive capacity research (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998) suggests that for knowledge transfer to take place, partnering firms in an alliance need to establish knowledge-sharing mechanisms that facilitate interactions between their personnel. These mechanisms are essential for KA because a significant part of technological knowledge is embedded in firm-specific processes (Teece and Pisano, 1994; Lane and Lubatkin, 1998) and can only be acquired through interactions between the individuals within the alliance partners (Dyer and Singh, 1998). For instance, although American car manufacturers such as GM were familiar with the principles of Japanese "lean manufacturing", GM was only able to benefit from lean manufacturing after forming the NUMMI alliance with Toyota that allowed for intensive interactions between GM and Toyota engineers (Inkpen, 2008). These arguments suggest that for KA to take place in an alliance, understanding how an alliance partner applies its capabilities is as important as understanding their meaning and value (Brown and Duguid, 2001). Therefore, while pre-existing technological overlap can enhance the assimilation of an alliance partner's knowledge, it in itself is not sufficient for facilitating KA (Dyer and Singh, 1998; Lane and Lubatkin, 1998).

In contrast, an accurate understanding of the meaning and commercial usefulness of an alliance partner's capabilities is sufficient for CS because in CS alliances, acquisition of partners' knowledge is neither required nor desired (Lubatkin *et al.*, 2001:1367). Instead, partnering firms in such alliances direct their efforts toward specializing in their own technological areas to contribute to the joint alliance outcome, rather than internalizing each other's knowledge. As Lubatkin, Florin, and Lane (2001 p.1367) put it, "*The participating firms need only learn enough about the other's knowledge to appreciate how to best link and leverage their respective competencies*." Pre-existing technological overlap can provide partnering firms in CS alliances with the necessary understanding about the nature and commercial potential of each other's knowledge (Cohen and Levinthal, 1990 p.136), as well as about how their complementary knowledge bases can be combined and commercially exploited (Mowery *et al.*, 2002). Based on the above arguments, we hypothesize that pre-existing technological overlap is more conducive to CS than to KA in alliances.

Hypothesis 1: Technological overlap is more strongly associated with complementary specialization than with knowledge acquisition in alliances.

Alliance experience and knowledge utilization

Besides technological overlap, alliance experience is another factor recognized by the literature to enhance a firm`s ability to effectively utilize external knowledge as it improves a firm`s know-how acquisition skills by exposing it to diverse sources of external knowledge (Anand and Khanna, 2000; Zollo *et al.*, 2002; Kale and Singh, 2007). Prior experience with a diverse set of alliance partners leads to a greater ability to develop shared inter-organizational routines that enable know-how transfer between alliance partners (Zollo *et al.*, 2002; Hoang and Rothaermel, 2005). Moreover, alliance experience improves firms' alliance management capabilities and facilitates better coordination with partners, which enhances inter-partner know-how transfers (Kale *et al.*, 2002; Sampson, 2005; Kale and Singh, 2007). The development of intra- and inter-organizational routines which enable firms to better manage their alliances and assimilate their alliance partners` knowledge in turn increases the speed with which firms learn in subsequent alliances (Anand and Khanna, 2000), and facilitates easier exchange of knowledge and technology (Sampson, 2005; Heimeriks and Duysters, 2007). In addition to know-how acquisition skills, alliance experience increases firms` opportunities to access and utilize external know-how. Firms with high levels of alliance experience are considered desirable alliance partners (Dyer and Singh, 1998), which implies that such firms have advantageous access to their partners' capabilities and associated know-how. Overall, these findings suggest that firms with a high degree of alliance experience can manage their future alliances better and face lower barriers to knowledge transfer from their alliance partners.

As we explain above, acquiring knowledge from alliance partners requires acquiring the associated know-how (Brown and Duguid, 2001). A primary reason that many American firms did not achieve their learning objectives in their alliances with Japanese partners, despite having opportunities to interact with them and observe how they applied their knowledge, was that they focused mostly on what their Japanese partners knew but neglected "*how and why they knew what they knew*" (Inkpen, 1998 p.74). While participating in the application of external knowledge is necessary for assimilating the know-how associated with it (Cohen and Levinthal, 1990; Inkpen, 2008; Janowicz-Panjaitan and Noorderhaven, 2008, 2009), it is not sufficient in itself, because the learning firm also needs to accurately analyze and interpret its learning experiences and create mechanisms for their internal application and diffusion. In the NUMMI alliance, for instance, GM initially struggled to benefit from the learning experiences of GM managers assigned to NUMMI because "*although these managers were learning as individuals, many became frustrated when they reentered GM because they were unable to implement the ideas they had learned from NUMMI. Within GM there was significant resistance to the Toyota production system (TPS) and a lack of understanding as to how GM could benefit from lean manufacturing*" (Inkpen, 2008 p.449). Only after a new top management team that actively supported learning from NUMMI took over and established mechanisms for systematically processing, codifying, and internally diffusing the knowledge transferred from NUMMI was GM able to internally apply, and benefit from, that lean manufacturing knowledge.

The above arguments suggest that a firm's know-how acquisition skills are determined by its awareness of the know-how associated with that external knowledge, along with its ability to systematically process its interactions with external knowledge sources and establish mechanisms that enable the internal diffusion and application of new knowledge. By increasing firms' awareness of their alliance partners' know-how, enhancing their ability to develop shared routines with their alliance partners, and reducing the barriers to knowledge transfer, alliance experience improves firms’ know-how acquisition skills and can enable firms in KA alliances to acquire the know-how associated with their partners’ capabilities and internally replicate it.

As summarized above, alliance experience enhances knowledge utilization in subsequent alliances by improving alliance management capabilities and reducing the barriers to knowledge transfer between alliance partners. While both of these benefits are relevant for KA alliances, only the former is applicable to CS alliances, because of the limited importance of knowledge transfer for CS. Knowledge exchange in CS alliances is only required for coordinating the alliance-related activities of partnering firms, so that they can be combined toward a joint commercial outcome (Lubatkin *et al.*, 2001; Lui, 2009). In CS alliances, partnering firms have neither the incentive nor the requirement to share their know-how with each other. In fact, knowledge exchange between partnering firms may be explicitly precluded in the design of CS alliances, enabling partnering firms to protect their know-how (Mowery *et al.*, 2002). Because of the relatively limited applicability of the benefits of alliance experience in CS alliances, we hypothesize that the experience of partnering firms in previous alliances is more conducive to KA than to CS in alliances.

Hypothesis 2: Alliance experience is more strongly associated with knowledge acquisition than with complementary specialization in alliances.

Thus far, we have argued that technological overlap is more conducive to CS and alliance experience is more conducive to KA in alliances. Since both technological overlap and alliance experience are important determinants of firms` external knowledge utilization abilities, we propose that they do not affect the outcomes of external knowledge utilization independently of each other. Specifically, while technological overlap itself is not sufficient for facilitating know-how transfer, it may enhance the efficiency of know-how-transfer mechanisms in KA alliances for at least two reasons. First, technological familiarity reduces the time and effort, and hence the cost, of evaluating alliance partners' knowledge (Kim and Inkpen, 2005). Thus, firms with overlapping technological capabilities can benefit more from their interactions with their alliance partners since they can use these opportunities to understand the more subtle aspects of their partners' knowledge, rather than having to understand its meaning. Second, familiarity with the technological aspects of an alliance partner's knowledge implies familiarity with the logic and assumptions underlying that partner's capabilities (Lane and Lubatkin, 1998). Such familiarity can improve firms' understanding of the know-how associated with alliance partners' capabilities since it enables them to better comprehend "*how and why their partners know what they know*" (Inkpen, 1998 p.74). Thus, we suggest that as technological overlap between alliance partners increases, the relationship between alliance experience and KA becomes stronger.

Hypothesis 3: Technological overlap positively moderates the relationship between alliance experience and knowledge acquisition in alliances.

METHODOLOGY

Sample and data sources

We drew our sample of alliances from the Securities Data Company (SDC) database. SDC collects alliance-related information from publicly available sources, has tracked alliances since the early 1990s, and provides one of the major databases used by researchers to study alliances (Schilling, 2009). Following the literature on technology-driven interfirm collaboration (*e.g.* Mowery *et al.*, 1996; Colombo *et al.*, 2006; Nooteboom *et al.*, 2007; Hoang and Rothaermel, 2010; Vasudeva and Anand, 2011), we used patent data to measure firm capabilities. Patents reflect R&D capabilities and provide a disaggregated measure for tracking capability development as a result of strategic choices, such as alliance participation (Mowery *et al.*, 1996). Therefore, a firm's patent portfolio can be seen as a reflection of its technological capability portfolio. We obtained patent data from the National Bureau of Economic Research (NBER) (Hall *et al.*, 2001), which provides data on patents and patent citations for all patents granted by the US Patent and Trademark Office from 1976 to 2006. We obtained financial data for our sample firms from the Compustat database.

To construct our sample, we identified in the SDC database two-partner alliances formed from 1996 to 2000 (five years) for which the partners and their ultimate parents were included in the NBER database as patent assignees. Focusing on alliances between patent-holding firms provides a setting in which the utilization of external technological knowledge through KA and CS is important. Requiring that the ultimate parents be patent assignees provides a control for the possibilities that technological capabilities diffuse through corporate entities and are shaped by the patents in the entire corporate structure (Mowery *et al.*, 1996).

A total of 1,647 alliances in as many as 49 two-digit SIC codes[1] were recorded in the SDC database for our sampling period, with patent data for the partnering firms and their parents. Of these, 1,072 were formed in four industries: chemicals; electronic equipment; business services; and engineering, accounting, and management services.[2] In order to limit industry-specific influences, we focused on alliances in these four industries, which accounted for 65 percent of all alliances during our sampling period. After excluding 97 alliances that had

[1] SDC assigns an SIC code to each alliance based on the nature of the alliance activity.
[2] These industries are represented by the two-digit SIC codes 28, 36, 73, and 87, respectively.

missing financial or patent information and four alliances formed between partners under the same corporate structure, we tested our hypotheses on a sample of 971 alliances.

Dependent variable

Our categorical dependent variable *Alliance type* takes the value of 0 for alliances that exhibit neither KA nor CS, 1 for those that exhibit CS, and 2 for those that exhibit KA. We used the technological similarity measure developed by Jaffe (1986) to measure KA and CS in alliances, based on the correlation between the patent portfolios of alliance partners and calculated with the following formula:[3]

$$P_{ij} = F_i F`_j \,/\, [(F_i F_j)\,(F_{ji})]^{1/2},$$

where P_{ij} is the technological similarity between two patent portfolios, F_i is the vector of technological capabilities for Firm *i*, and F_j is the vector of technological capabilities for Firm *j*. The vector F is represented by (F_1, F_2, F_3....F_k), where F_k is the number of patents in NBER patent class *k.*

This similarity measure ranges from 0 to 1, such that 0 represents complete dissimilarity and 1 represents complete overlap between the two patent portfolios. We then subtracted the similarity values from 1 to calculate the technological distance between two patent portfolios (Vasudeva and Anand, 2011). For each alliance, we calculated and compared the technological distance between the patent portfolios of partnering firms' as of one year before and five years after the alliance formation to determine how their technological capabilities developed with respect to each other in the course of the alliance. A decreasing technological distance after the

[3] In 100 of the alliances in our sample, one of the alliance partners did not have any patents prior to the alliance. In these cases, we assumed a pre-alliance technological distance of 1. We repeated our analyses by excluding these alliances, but our results remained robust.

alliance formation signifies convergence between the partners' technological capabilities and is an indicator of knowledge spillovers (Jaffe, 1986) and KA (Nakamura *et al.*, 1996). Consequently, alliances in which the technological distance between the partners' patent portfolios decreased after the alliance formation are classified as *KA alliances*.

Measuring CS was a more challenging task because of the multidimensional nature of the construct. While an increasing technological distance between the partners' patent portfolios after the alliance formation indicates a divergence of technological capabilities and the absence of KA (Nakamura *et al.*, 1996; Mowery *et al.*, 2002), we performed an additional analysis using the complementarity measure developed by Makri, Hitt, and Lane (2010) to evaluate whether this divergence unfolded in a complementary or random way. Following Makri, Hitt, and Lane (2010), we measured the technological complementarity between partnering firms in a focal alliance by their patents in the same subcategory, but different patent classes. The US Patent and Trademark Office classifies patents into 417 three-digit classes. Hall, Jaffe, and Trajtenberg (2001) further aggregate these 417 classes into 37 subcategories and six main categories in the NBER Patent Data Project. Each class belongs to only one subcategory. We measured the degree of complementarity by the number of successful patent applications of alliance partners in the same subcategory but different classes, divided by their total number of successful patent applications. For each alliance, we separately computed the degree of complementarity between the pre-alliance patent portfolios of the alliance partners and their patent stock accumulated during the five years following the alliance formation. We classified alliances in which both the technological distance and the complementarity between the partners increased after the alliance was formed as *CS alliances*.

In our sample, 645 alliances were classified as KA alliances and 121 as CS alliances. In the remaining 205 alliances, the post-formation developments of the partnering firms' technological capability portfolios did not exhibit an observable pattern in terms of knowledge utilization through either KA or CS. In these alliances, the technological distance between alliance partners either did not change or increased without being accompanied by an increase in complementarity. Although knowledge exchange and utilization can also take place in alliances without being reflected in the development of technological capability portfolios, our rather conservative empirical approach did not allow us to determine the type and nature of knowledge utilization occurring in these alliances, so we classified them in the residual "other" category.

Independent variables

Since our unit of analysis is a focal alliance, we constructed our independent variables at the alliance level. This approach is consistent with our conceptualization of KA and CS as alliance-level outcomes, as well as with previous research in this area (Mowery *et al.*, 1996, 2002).

Technological overlap We measured the overlap in technological capabilities between alliance partners by their reciprocal patent citations using the "cross-citation rate" measure developed by Mowery, Oxley, and Silverman (1996, 1998). When a firm obtains a patent for a technological innovation, it cites all the previous patents on which that innovation is based (Mowery *et al.*, 1996). The proportion of citations to a particular firm's patents in a focal firm's patents represents the degree to which the focal firm drew on the other firm's knowledge to develop its technological capabilities. Therefore, to the extent two firms cite each other's patents, their technological capabilities are assumed to overlap (Mowery *et al.*, 1996, 1998). The *Pre-*

alliance cross-citation rate variable was calculated with the following formula and expressed in percentage points for easier interpretation:

Cross-citation rate$_{AB}$ *= (Citations in Partner A's patents to Partner B's patents) / (Total citations in Partner A's patents) + (Citations in Partner B's patents to Partner A's patents) / (Total citations in Partner B's patents).*

Alliance experience We constructed the *General alliance experience* variable as the total number of alliances established individually by the partnering firms during the five years preceding a focal alliance. Using a five-year window to measure experience is consistent with prior research in this area (Heimeriks and Duysters, 2007). Five years is considered the average period during which the effects of an alliance impact a firm's overall alliance experience (Heimeriks and Duysters, 2007). To accurately assess the exposure of firms to diverse sources of external knowledge, we excluded multiple prior collaborations with the same partners from the general alliance experience count.

Control variables

General alliance experience ratio To control for the possibility that firms with similar levels of alliance experience may be more likely to form an alliance and to account for the imbalance between the levels of alliance experience among partnering firms in a focal alliance, we included the variable *General alliance experience ratio* in our models, which is the ratio of the partners' general alliance experience counts.

Partner-specific alliance experience We controlled for any prior collaboration experience between alliance partners to account for pre-existing dyad-specific knowledge-sharing routines

(Zollo *et al.*, 2002) and other relation-specific assets (Dyer and Singh, 1998). The *Partner-specific alliance experience* variable is the number of alliances that the partnering firms in a focal alliance established with each other in the five years preceding the focal alliance, excluding the year of formation.

Pre-alliance technological complementarity We controlled for path dependence in the complementary capability development with the *Pre-alliance complementarity* variable, which indicates in percentage points the degree of technological complementarity between the partnering firms in a focal alliance before they entered into the alliance.

Alliance size Since large firms have more resources to devote to capability development and are likely to have more alliance experience (Kale *et al.*, 2002), we controlled for alliance size by including the variable *Alliance total assets*, which is the natural logarithm of the combined total assets of the partnering firms in a focal alliance[4] in the alliance formation year.

Alliance governance form We controlled for the governance mode of a focal alliance because equity alliances allow for more interaction and opportunities for capability development than non-equity alliances (Anand and Khanna, 2000). The *Joint venture dummy* binary control variable has a value of 1 if the alliance is a joint venture and 0 otherwise.

Industry relatedness We controlled for non-technological overlaps of capabilities between the partnering firms in a focal alliance with the *Same industry* binary variable, which has a value of 1 if the partners have the same four-digit SIC code and 0 otherwise.

[4] We also tested our models by including a ratio of the partners' total assets to control for size imbalances between partners and by measuring alliance size by the total sales of the partnering firms, but the results remained robust.

International alliances We controlled for the challenges faced by firms that ally with international partners (Lavie and Miller, 2008) with the *International* binary variable, which is coded as 1 if the partners are from different countries and 0 otherwise.

We took industry effects into account with dummy variables for each two-digit alliance SIC code. Lastly, we controlled for any possible effects specific to a given alliance-formation year by including dummy variables for these years.

Empirical analysis

We used a multinomial logistic regression model with the "other" category as the baseline. It separately compared the effects of pre-alliance technological overlap and alliance experience on the likelihood of KA and CS occurring in an alliance. The *Pre-alliance cross-citation rate* and *General alliance experience* variables were mean-centered to decrease the collinearity between their first- and second-order terms. We tested Hypothesis 3 with the interaction term between *Pre-alliance cross-citation rate* and *General alliance experience*. All models were estimated with heteroskedasticity-robust standard errors. Multinomial logistic regression relies on the assumption that the outcome alternatives are independent (Long and Freese, 2001), and this was both conceptually and empirically satisfied in our setting.[5] Our sample of 971 observations also meets the sample-size requirements[6] of the maximum-likelihood estimator used by logistic regression models (Long, 1997).

[5] We employed a likelihood-ratio test to confirm that the outcome variables were distinct from one another (Long and Freese, 2001).
[6] Maximum-likelihood estimation requires a sample of at least 100 observations; samples with more than 500 observations are considered adequate (Long, 1997:54).

RESULTS

Descriptive statistics

Table 1 presents the descriptive statistics and pairwise correlations. To ensure that our estimation was not affected by multicollinearity among the predictor variables, we checked the variance inflation factors (VIF) of our variables. All VIFs are below the commonly accepted threshold of 10 (Studenmund, 2010). We therefore concluded that our results were not affected by multicollinearity.

We begin by describing the salient features of our sample. Descriptive statistics suggest that we have a highly heterogeneous sample with respect to all variables. Pre-alliance cross-citation rate ranges between 0 and 4.45 percent, with a mean of 0.19 percent and a standard deviation of 0.56 percent, suggesting that the pre-alliance degree of technological overlap between alliance partners varies highly across our sample. The combined alliance experience of partnering firms in our sample are between 0 and 515. The dyad with the largest combined alliance experience in our sample was formed between IBM and Motorola, Inc. in 1997. In addition to the two alliances these two firms had with each other, IBM participated in 368 other alliances and Motorola in 146 from 1992 to 1996, according to the SDC database. The relatively high standard deviation of Partner alliance experience ratio (0.248) compared to the mean (0.165) suggests that in many of our sample alliances partnering firms have a rather unbalanced levels of prior alliance experience. The mean of Partner specific alliance experience is 0.156, indicating that most of the alliances in our sample are novel-partner alliances for partnering firms (the partnering firms in 93 - out of 971 - alliances in our sample have a prior collaboration experience with each other ,in the five years preceding the focal alliance). The dyad with the greatest number of prior collaborations was Hewlett Packard and Microsoft Corporation, with eight alliances with each other from 1992 to 1996. Pre-alliance complementarity ranges from 0 to 100 percent, indicating a high variance in terms of prior knowledge base relatedness of alliance partners in our sample. Our dummy variables show that approximately 10 percent of our sample alliances are joint ventures, 21 percent are formed by firms having the same primary 4-digit SIC code, and 28 percent are formed by firms from different countries.

Regression results

Table 2 presents the results of multinomial logistic regressions. Model 1 includes control variables only, Model 2 includes the main effects of the independent variables *Pre-alliance cross-citation rate* and *General alliance experience*, Model 3 adds the interaction term between *Pre-alliance cross-citation rate* and *General alliance experience* to Model 2. The control variables offer interesting insights. *Pre-alliance complementarity* is negatively and significantly associated with the likelihood of CS across all models. This finding implies that CS is more likely to occur among alliance partners with unrelated knowledge bases. This is in line with the consensus in the literature that alliances are instrumental in exploiting potential complementarities. *Same industry* is positive and significant for KA across all models, implying that KA is a more common strategy in alliances between firms in the same industry than CS is.

Table 1 – Descriptive statistics and correlation matrix

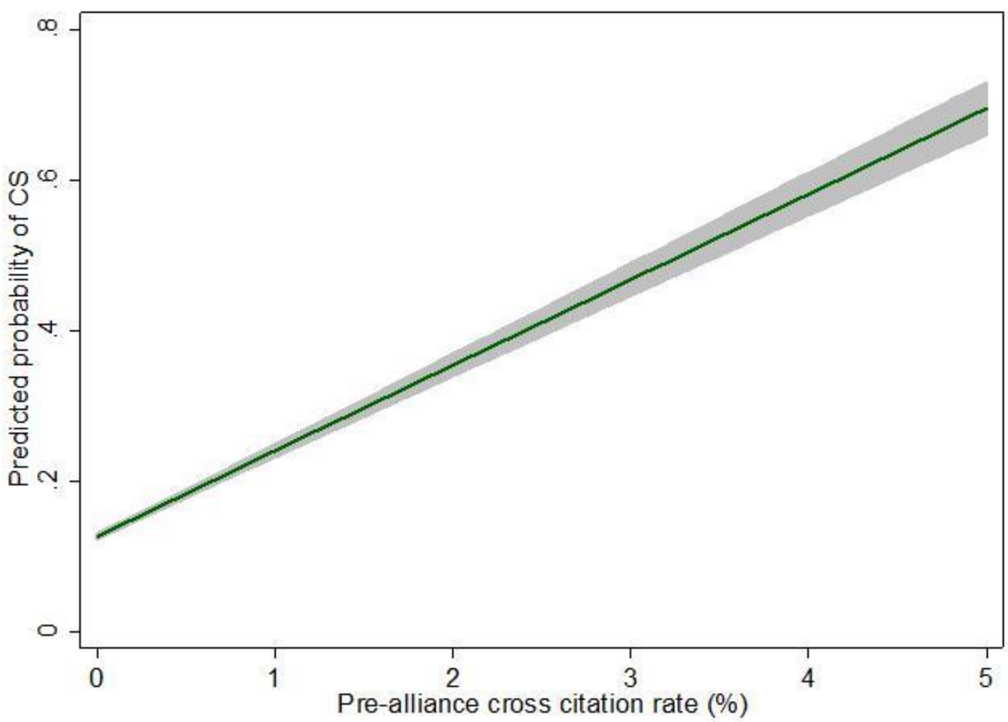
	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Alliance type*	1.453	0.819	0.000	2.000	1.00									
(2) Pre-alliance cross-citation rate (%)	0.194	0.556	0.000	4.453	-0.02	1.00								
(3) General alliance experience	81.648	104.444	0.000	515.000	0.15	0.31	1.00							
(4) Partner alliance experience ratio	0.165	0.248	0.000	0.958	0.03	0.28	0.07	1.00						
(5) Partner specific alliance experience	0.156	0.656	0.000	8.000	0.06	0.23	0.39	0.26	1.00					
(6) Pre-alliance complementarity in %	19.504	19.334	0.000	100.000	0.07	-0.14	-0.03	0.02	0.01	1.00				
(7) Joint venture	0.102	0.303	0.000	1.000	-0.00	0.13	0.02	0.08	0.03	-0.01	1.00			
(8) Same industry	0.214	0.410	0.000	1.000	0.02	-0.06	-0.18	0.01	-0.05	0.07	-0.08	1.00		
(9) International	0.284	0.451	0.000	1.000	0.01	0.04	0.02	0.04	0.00	0.04	0.13	-0.05	1.00	
(10) LN(Alliance total assets)	16.012	2.062	9.303	20.633	0.14	0.25	0.55	0.08	0.17	0.01	0.16	-0.26	0.25	1.00

*Alliance type equals to 0 for alliances classified as “other”, 1 for CS alliances, and 2 for KA alliances.

All correlations above 0.05 are significant

H1 suggests that technological overlap has a statistically more significant impact on CS than on KA. In Models 2 and 3, the coefficient of *Pre-alliance cross-citation rate* is positive and significant for CS and insignificant for KA, supporting H1. We computed the predicted probabilities of the alliance type outcomes in order to more easily interpret our findings.[7] The predicted probability of CS occurring in an alliance is 0.11 at the mean value of *Pre-alliance cross-citation rate*, 0.15 at one standard deviation above the mean, and 0.66 at the maximum value. The graph in Figure 1 illustrates the relationship between technological overlap, measured by *Pre-alliance cross-citation rate*, and the likelihood of CS in an alliance.

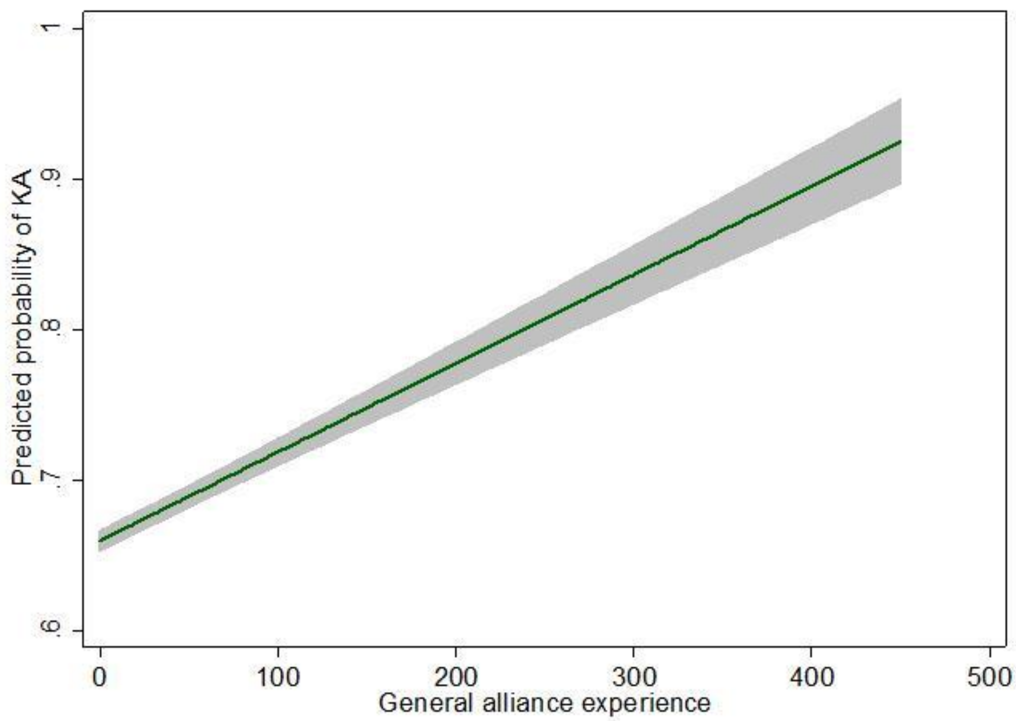
Figure 1 - Technological overlap and the likelihood of CS with 95% confidence intervals



[7] We computed the predicted probabilities using the *Margins* command in Stata 11. This command returns the average predicted probability of an outcome by calculating the predicted probability for each observation in the sample at specified levels of the independent variables, while holding the other variables at their means.

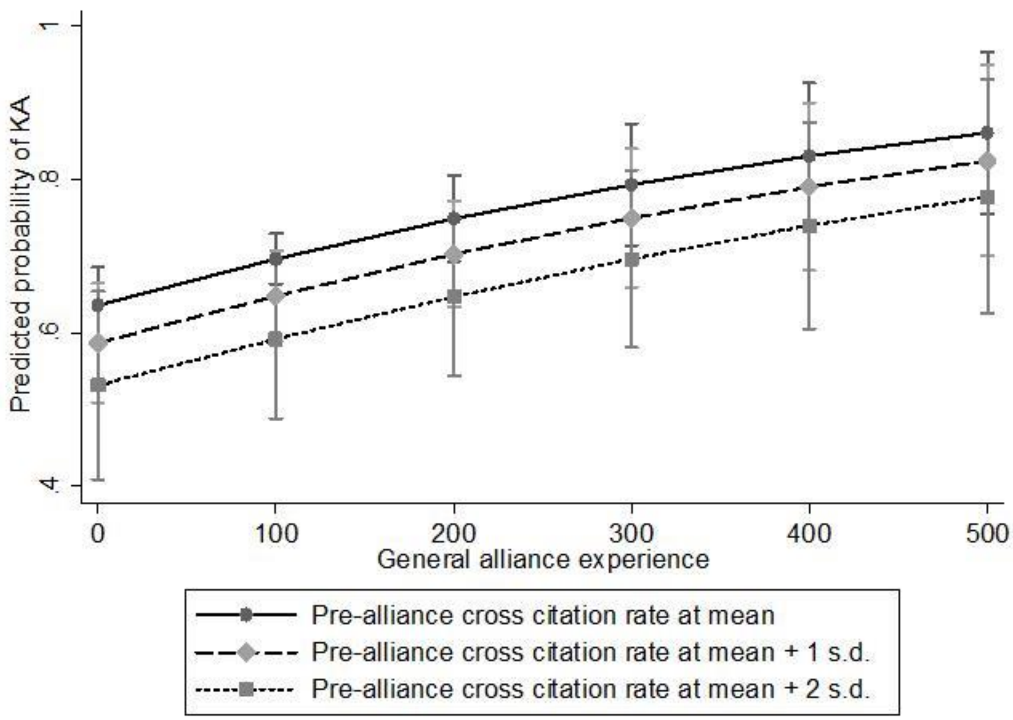
H2 suggests that alliance experience has a statistically more significant impact on KA than on CS. In Models 2 and 3, the coefficient of *General alliance experience* is positive and significant for KA and insignificant for CS, supporting H2. The predicted probability of KA occurring in an alliance is 0.68 at the mean value of *General alliance experience*, 0.74 at one standard deviation above the mean, and 0.87 at the maximum value. The graph in Figure 2 illustrates this relationship.

Figure 2 - Alliance experience and the likelihood of KA with 95% confidence intervals



H3 suggests that at high levels of technological overlap, the relationship between alliance experience and KA becomes stronger. In Model 3, the interaction term *Pre-alliance cross.cit. rate X Gen. alliance exp.* is insignificant for CS but negative and significant for KA. This result suggests that, contrary to our prediction, at high levels of technological overlap the relationship between alliance experience and the likelihood that the alliance culminates in KA becomes weaker, rather than stronger. We elaborate further on this in the discussion section. The graph in Figure 3 illustrates the relationship between alliance experience and the likelihood of an alliance culminating in KA at different levels of technological overlap.

Figure 3 - Alliance experience and the likelihood of KA at different levels of technological overlap with 95% confidence intervals



Supplementary analyses

We performed additional analyses to confirm the robustness of our results. First, we measured the effects of technological overlap and alliance experience on KA and CS in alliances using continuous measures and employing Tobit estimations. Second, we performed our empirical tests by including only KA and CS alliances in the sample and using a binary logit model with CS alliance type as the dependent variable. This allowed us to test the effects of our independent variables on the likelihood of CS against that of KA, rather than against the residual "other" category. Third, we reconstructed our technological overlap variable by using the proportion of alliance partners' patents in the same patent classes to all of their patents as an alternative measure. This alternative measurement is based on the contention that if patents reflect technological capabilities, the ability to successfully patent in the same narrowly defined technological areas implies similar technological capabilities. Fourth, in order to exclude the possible effects of specific firms and dyads occurring multiple times in our data, and the possibility that our results were being driven by firm- and dyad-specific factors, we clustered the standard errors by partner firm and by dyad. We also performed our tests with the exclusion of dyads that had more than one alliance in our sampling period. Across all specifications our results remained robust.

In addition, we tested our model by including the squared terms of our independent variables in our models to account for the possible effect of diminishing returns on the impact of technological overlap[8] and alliance experience[9] on CS and KA in Model 4. While the coefficient of *Pre-alliance cross-citation rate squared* is not significant for CS and KA, the coefficient of *General alliance experience squared* is negative and significant for KA, suggesting that the influence of general alliance experience on the likelihood of KA in an alliance is subject to diminishing returns. This implies that the benefits of general alliance experience for know-how acquisition decrease at higher levels of experience, which can be due to competency traps (Hoang and Rothaermel, 2005; Sampson, 2005) and the erroneous generalization of earlier

[8] As technological overlap increases, the partners' knowledge bases can become increasingly similar, rather than complementary, which may decrease the feasibility of CS in an alliance.

[9] Inappropriate generalization of know-how acquisition skills developed in prior alliances (Haleblian and Finkelstein, 1999) or participation in alliances with redundant gains (Hoang and Rothaermel, 2005) may negatively affect the benefits of alliance experience on knowledge utilization in future alliances.

experience (Haleblian and Finkelstein, 1999). The inflection point for the inverted U-shaped relationship between alliance experience and the likelihood of KA occurs when *General alliance experience* equals 250. This is within the range of our data, and the partnering firms in 68 alliances from our sample have a combined alliance experience greater than 250.

Table 2 - Multinomial logistic regression predicting alliance type

	Model 1		Model 2		Model 3		Model 4	
Dependent variable	CS	KA	CS	KA	CS	KA	CS	KA
General alliance experience ratio	0.220	0.102	-0.175	0.237	-0.149	0.244	-0.234	0.161
	(0.475)	(0.365)	(0.531)	(0.376)	(0.532)	(0.376)	(0.551)	(0.386)
Partner-specific alliance experience	0.494*	0.376	0.295	0.196	0.322	0.218	0.274	0.284
	(0.276)	(0.255)	(0.265)	(0.234)	(0.279)	(0.245)	(0.272)	(0.235)
Pre-alliance complementarity (%)	-0.018***	0.006	-0.014**	0.005	-0.013**	0.005	-0.013**	0.004
	(0.007)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)
Joint venture dummy	0.636*	0.063	0.600	0.119	0.601	0.100	0.554	0.083
	(0.356)	(0.296)	(0.368)	(0.296)	(0.366)	(0.297)	(0.365)	(0.298)
Same industry dummy	0.494*	0.432**	0.505*	0.466**	0.507*	0.470**	0.475	0.484**
	(0.300)	(0.212)	(0.302)	(0.211)	(0.301)	(0.213)	(0.306)	(0.216)
International dummy	-0.168	-0.161	-0.089	-0.122	-0.089	-0.093	-0.113	-0.094
	(0.275)	(0.201)	(0.282)	(0.203)	(0.279)	(0.200)	(0.285)	(0.203)
LN (Alliance total assets)	0.099	0.187***	0.013	0.122**	0.028	0.105*	0.023	0.068
	(0.063)	(0.045)	(0.071)	(0.055)	(0.070)	(0.054)	(0.072)	(0.055)
Pre-alliance cross-citation rate (%)			0.515**	-0.190	0.550**	0.041	1.327**	-0.603
			(0.202)	(0.223)	(0.267)	(0.257)	(0.556)	(0.431)
General alliance experience			0.002	0.003**	0.001	0.004***	4.24e-4	0.009***
			(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
Pre-alliance cross.cit. rate X Gen.alliance exp.					-0.000	-0.003**		
					(0.001)	(0.001)		
Pre-alliance cross-citation rate squared							-0.293	0.199
							(0.215)	(0.131)
General alliance experience squared							-1.11e-6	-2.6e-5***
							9.74e-6)	(7.54e-6)
Constant	-1.910*	-2.445***	-0.531	-1.391	-0.790	-1.075	-0.657	-0.317
	(1.036)	(0.721)	(1.188)	(0.898)	(1.174)	(0.890)	(1.257)	(0.938)
Observations	971		971		971		971	
Log likelihood	-797.57427		-785.48301				-771.047	
Wald Chi^2	68.02***		86.59***				131.81***	

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All models include year and industry dummies. All significance tests are two-tailed.

DISCUSSION

In this paper we investigate the role of two factors that are recognized to influence firms` external knowledge utilization abilities, namely technological overlap and alliance experience, in facilitating KA and CS in alliances and find that they technological overlap enhances CS and alliance experience enhances KA. Contrary to H3, our results show that at high levels of technological overlap, alliance experience is less, rather than more, conducive to KA. A possible explanation for this surprising finding is that alliance partners sharing a high degree of technological overlap are more likely to be protective of the non-overlapping portion of their knowledge bases because they are likely to draw on the same technological areas to develop their commercial products. They may thus and may seek to prevent outbound knowledge spillovers to each other to avoid the exploitation of their knowledge-based assets and eventual cannibalization of their competitive positions in product markets (Hamel *et al.*, 1989; Hamel, 1991; Dussauge *et al.*, 2000). To avoid knowledge appropriation by their partners, firms in these alliances may explicitly restrict knowledge-exchange provisions when designing and executing their alliances (Mowery *et al.*, 2002; Inkpen, 2008). Restricted opportunities to observe and ultimately assimilate know-how can prevent KA as an outcome in these alliances, even though partnering firms have developed know-how acquisition skills through previous alliances. This also suggests that CS is a more feasible knowledge utilization strategy in these alliances, which is consistent with our findings.

Contributions to the literature

We make several contributions to the literature. Most importantly, we contribute to the literature in knowledge utilization and learning in alliances by extending the study of Mowery, Oxley, and Silverman (2002) and providing a more thorough analysis of the relationship between antecedents of external knowledge utilization and its outcomes in the form of KA and CS in alliances. Our analysis also reinforces the viability of CS as an alternative external knowledge utilization strategy to KA (Inkpen and Tsang, 2007). While we acknowledge that CS alliances are completely devoid of inter-partner knowledge transfers, We suggest that knowledge transfers in these alliances should be seen from the perspective of the development of complementary capabilities, rather than as an attempt to acquire the partner's knowledge (Nakamura *et al.*, 1996; Lubatkin *et al.*, 2001; Grant and Baden-Fuller, 2004). The overwhelming emphasis on KA as the primary knowledge utilization strategy in alliances has somewhat excluded other knowledge utilization strategies, such as CS, from the focus of management research. Consequently, from an organizational learning standpoint, alliances in which there is no observable acquisition of knowledge from partners may be considered unsuccessful (*e.g.* Hamel *et al.*, 1989; Inkpen, 1996; Inkpen and Tsang, 2007). Our findings suggest that a subset of such alliances could be characterized as CS alliances and that the partners' post-alliance capability development should be seen in this light.

We also make an empirical contribution by providing a unique measure for CS in alliances that takes both the relative distance and the technological complementarity between alliance partners' capabilities into account. CS is an under-researched construct and has no established operationalization. In their seminal study, Mowery, Oxley, and Silverman (2002) measured CS by the negative change in the cross-citation rate between partnering firms after alliance formation. Although this approach measures divergence, it relies on the strong assumption that such divergence occurs in a complementary rather than a random way. We take previous efforts to measure CS (Nakamura *et al.*, 1996; Mowery *et al.*, 2002) one step further by combining a well-founded measure for complementarity (Makri *et al.*, 2010) with an established measure for technological similarity (Jaffe, 1986). Our combined measure adequately addresses the conceptualization of CS alliances as "alliances in which partner capabilities become more dissimilar, yet in a complementary way" (Nakamura *et al.*, 1996; Mowery *et al.*, 2002) and enables future empirical testing of theoretical advances in this research stream (*e.g.* Grant and Baden-Fuller, 2004; Hennart and Zeng, 2005).

Our results also have implications for the research streams in absorptive capacity and alliance experience. For the absorptive capacity research, our results show that, in line with Mowery *et al.* (2002), CS as a knowledge utilization outcome is enhanced by technological overlap, which is recognized as an important precedent of partner-specific absorptive capacity (Dyer and Singh, 1998; Lane and Lubatkin, 1998; Mowery *et al.*, 2002). Our findings thus suggest that, besides the generally accepted association between absorptive capacity and KA (*e.g.* Cohen and Levinthal, 1990; Lane and Lubatkin, 1998), absorptive capacity is also beneficial to the development of complementary capabilities in alliances in which do not culminate in inter-partner knowledge acquisition. In other words, absorptive capacity has also "non-absorptive" benefits to partnering firms in alliances. This underlines the multidimensionality of the construct (Zahra and George, 2002; Ebers and Maurer, 2014) and emphasizes the importance of differentiating between its knowledge evaluation and knowledge acquisition components. We contribute to the research on alliance experience by empirically showing that, besides improving alliance management capabilities (*e.g.* Sampson, 2005; Heimeriks and Duysters, 2007; Kale and Singh, 2007) and alliance performance (*e.g.*Zollo *et al.*, 2002; Hoang and Rothaermel, 2010; Schilke and Goerzen, 2010), such experience facilitates the acquisition of technological knowledge from alliance partners. Altogether, our study contributes to the understanding of alternative firm innovation strategies through alliances.

Limitations and future research

Our study also has limitations that could be addressed by future research. First, we rely on the change in alliance partners' patent portfolios to determine the knowledge utilization strategies of partnering firms an alliance. While patents are widely acknowledged to represent firms' technological capabilities (*e.g.* Mowery *et al.*, 1996; Colombo *et al.*, 2006; Nooteboom *et al.*, 2007; Hoang and Rothaermel, 2010; Vasudeva and Anand, 2011), they are *ex-post* measures of technological capability development. Thus, in an alliance context, measuring the utilization of technological knowledge through the change in patent portfolios requires the assumption that the patenting activity after the alliance formation is in line with the strategic goals of partnering firms in that alliance. Although there is strong support for this assumption in the literature (*e.g.* Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Colombo, 2003; Colombo *et al.*, 2006), future research can supplement patent-based analyses with *ex-ante* measures of alliance strategies to increase the robustness of such analyses.

Second, although we provide a unique measure for CS, measuring complementarity based on patenting activity has inherent limitations. First, an element of arbitrariness is involved in aggregating patent classes into broader subcategories (Hall *et al.*, 2001). Second, certain classes in a subcategory may be more complementary with one another than with other classes in that subcategory. Third, complementarities may exist between patent classes across subcategories. A more fine-grained analysis of patents and their classification could address these limitations and lead to the development of a stronger measure for CS.

Another limitation of our empirical strategy is that, to analyze the impact of alliance experience on knowledge utilization, we focus on the number of previous alliances established by partnering firms and do not consider whether these alliances were of KA or CS type. Nor do we account for other possibly relevant previous alliance attributes (*e.g.*, equity versus non-equity governance forms). However, experience in different types of alliances may have different effects on the knowledge utilization patterns in a focal alliance (Duysters *et al.*, 2012). Future research could address this limitation by using more sophisticated measures of alliance experience.

Somewhat surprisingly, we find no statistically significant association between technological overlap and KA, which is consistent with the lack of support for H3 but contradicts prior research in this area (Mowery *et al.*, 1996, 1998, 2002). Our supplementary analyses suggest that this divergent finding results from the different empirical strategies used in this study and in prior work: while we measure KA by the decrease in technological distance between the patent portfolios of partnering firms following the alliance formation, Mowery *et al.* rely on the post-formation increase in the reciprocal patent citations of partnering firms. Although patent citations have been commonly used in prior research to measure knowledge flows across firms (*e.g.* Mowery *et al.*, 1996, 1998, 2002; Rosenkopf and Almeida, 2003), we believe that technological distance provides a better operationalization for KA because the high correlation between pre- and post-alliance patent citations indicates a potentially spurious relationship between them, resulting from path-dependence in patent-citation behavior rather than genuine knowledge flows between alliance partners. Future research can resolve this divergence by developing more rigorous measures for KA.

There are also other promising avenues for future research. First, researchers could examine whether or not there are industry-level influences on the type of knowledge utilization in alliances. Second, they could investigate the performance implications of experience in KA and CS alliances. Third, they could analyze whether KA and CS are substitutes for, or complementary to, one another in firms' efforts to access external knowledge through corporate development activities other than alliances (*e.g.*, mergers and acquisitions).

Managerial implications

Our research also points to some important managerial implications. First, our findings show that firms seeking CS with an alliance partner are most likely to be successful if their technological capabilities sufficiently overlap with those of their partners. Therefore, managers should screen their potential alliance partners in terms of technological overlap when making alliance formation decisions. While the importance of such overlap for a CS alliance may not be intuitively clear due to the limited knowledge transfer requirements of these alliances, our analyses suggest that an overlap of technological capabilities is critical to learning *with* alliance partners and achieving CS. Second, our results point to the importance of exposure to diverse sources of external knowledge in the development of know-how acquisition skills, as well as to potential outbound know-how spillovers when alliance partners have a high level of alliance experience. This finding suggests that managers should be wary when forming alliances with highly experienced partners to protect themselves from such spillovers.

CHAPTER 4

LEARNING TO LEARN OR LEARNING TO COORDINATE? THE INFLUENCE OF ALLIANCE EXPERIENCE ON ACQUISITION PERFORMANCE

ABSTRACT

We examine how alliance experience influences acquisition performance through the transfer of knowledge utilization routines. We suggest that knowledge acquisition alliances, which facilitate knowledge acquisition from alliance partners, enhance firms` knowledge integration routines whereas complementary specialization alliances, which facilitate knowledge access without acquisition, improve knowledge combination routines. Drawing on transfer theory, we argue that the effects of alliance experience on acquisition performance depend on the congruence between the knowledge utilization goals in alliances and acquisitions. As predicted, we find that performance of acquisitions in the semiconductor industry, which require knowledge integration, is affected negatively by experience in complementary specialization alliances, while performance of acquisitions in the pharmaceutical industry, which require knowledge combination rather than integration, is affected positively by experience in complementary specialization alliances, and negatively by experience in knowledge acquisition alliances.

Keywords: Learning, complementary specialization, acquisitions, alliances, experience

INTRODUCTION

In the last two decades mergers and acquisitions (henceforth referred to as *acquisitions*) have become increasingly important corporate development activities for accessing and utilizing external knowledge (Haleblian *et al.*, 2009), as tapping into outside sources for capability development is as important as internal R&D efforts to remain competitive (Porrini, 2004; Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012). Nevertheless, most acquisitions fail to create shareholder value (Haleblian *et al.*, 2009). Consequently, many researchers have focused their efforts to understand how firms learn to make successful acquisitions and investigated how prior acquisition experience influences subsequent acquisition performance (for a review see Barkema and Schijven, 2008). Drawing on transfer theory (Ellis, 1965; Cormier and Hagman, 1987; Novick, 1988), this research stream suggests that experience affects performance positively when the acquisitions in which the experience is gained are structurally similar to those it is applied, and negatively when the similarities are superficial rather than structural (Haleblian and Finkelstein, 1999; Finkelstein and Haleblian, 2002). Extending this research stream, scholars have more recently pointed out similarities between acquisitions and alliances and have begun to investigate experience spillovers from alliances to acquisitions that affect acquisition performance (Porrini, 2004; Zollo and Reuer, 2010).

Research examining the effects of general alliance experience on acquisitions offers conflicting arguments and findings. While Porrini (2004) suggests that alliance experience teaches firms how to integrate external knowledge, Zollo and Reuer (2010) show that alliance experience positively affects the performance in acquisitions which require little integration. A likely reason for these conflicting findings is that these scholars treat alliance experience as a homogenous construct. But alliances, like acquisitions, are undertaken for a variety of reasons such as pooling of complementary assets or undertaking joint R&D, manufacturing, or marketing (Kale and Singh, 2009). While alliances provide suitable mechanisms for knowledge exchange and integration (Nakamura *et al.*, 1996; Inkpen and Tsang, 2007), the degree and nature of such exchange and integration depends on the goals and activities in a given alliance (Mowery *et al.*, 1996, 2002; Inkpen and Tsang, 2007). An examination of transferability of alliance experience to the management of acquisitions therefore requires analyzing both the knowledge utilization practices employed in past alliances and those required in subsequent acquisitions. Such an analysis, to our knowledge, has not yet been done.

In terms of external knowledge utilization, research has largely focused on two distinct alliance types: knowledge acquisition (KA) alliances in which partner firms internalize each other's technological capabilities and complementary specialization (*CS*) alliances in which partner firms combine their distinct but complementary areas of expertise (Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Mowery *et al.*, 2002; Grant and Baden-Fuller, 2004). While KA alliances are geared towards knowledge transfer and organizational learning, CS alliances emphasize coordination and exploitation of complementarities. Consequently, experience in KA and CS alliances improve different sets of knowledge utilization routines, which in turn can affect the transferability of alliance experience to acquisitions. We examine the effects of experience in these two types of alliances, on acquisitions in two high technology industries, namely semiconductors and pharmaceuticals. These industries provide an ideal empirical setting to test our hypotheses as they differ in terms of the role of external technological knowledge in product development. We find evidence for positive as well as negative experience spillovers.

Our study highlights the context-dependent nature of the experience-performance relationship (Haleblian and Finkelstein, 1999; Finkelstein and Haleblian, 2002; Muehlfeld, Sahib, and Van Witteloostuijn, 2012) and offers two important theoretical contributions. First, we contribute to the research on experience spillovers by performing an in-depth analysis of structural similarities between alliances and acquisitions in terms of external knowledge utilization. Extant research implies that alliance experience, regardless of the nature and type of alliances comprising such experience, has performance implications in certain types of acquisitions (Porrini, 2004; Zollo and Reuer, 2010). We however show that such performance implications are contingent not only on the characteristics of acquisitions, but also on those of the alliances. Second, we contribute to the research on acquisition performance. By analyzing the properties of alliances and acquisitions in terms of knowledge utilization and demonstrating the conditions under which positive as well as negative experience spillovers materialize, we contribute to the efforts of researchers in this area to identify contingencies that distinguish successful acquisitions from unsuccessful ones (Barkema and Schijven, 2008; Haleblian *et al.*, 2009; Schijven and Hitt, 2012). Our findings also provide important guidelines to managers to shape their corporate development strategies.

THEORY AND HYPOTHESES

Experience spillovers across alliances and acquisitions: Prior research

Experience spillovers materialize when experience gained in one activity is transferred to a similar subsequent activity (Zollo and Reuer, 2010). Research on "transfer effects", *i.e.* the transfer of experience in prior events into performance in subsequent events, is initiated by psychology scholars who recognized that individuals, when developing solutions to the problems they face, typically draw on their past experience in similar events (Cheng *et al.*, 1986; Novick, 1988). Early research in this area suggests that prior experience can influence subsequent performance positively as well as negatively (Cormier and Hagman, 1987), depending on the similarity between the prior and subsequent events (Gick and Holyoak, 1987). Specifically, prior experience influences subsequent performance positively when prior and subsequent events are similar in their structural, solution-related features, but negatively when they share similarities in their salient, superficial features but are structurally different (Novick, 1988).

The subsequent application of transfer theory at the organizational level by management researchers shows that also at the level of organizations prior experience is generalized to subsequent events. In the same way that individuals develop habits and skills based on their experience, organizations develop routines (Nelson and Winter, 1982; Finkelstein and Haleblian, 2002) which are defined as `stable patterns of behavior that characterize organizational reactions to variegated, internal or external stimuli` (Zollo and Winter, 2002 p. 340). Acting as automated responses to situations organizations face, and allowing rapid transfer of experience to new situations (Cohen and Bacdayan, 1994), routines govern many operational as well as strategic organizational actions (Nelson and Winter, 1982; Winter, 1987). Although routines enhance organizational competence by allowing organizations to efficiently respond to many situations, they can also lead to erroneous generalization of experience causing negative performance implications. (Cohen and Bacdayan, 1994; Zander and Kogut, 1995). Erroneous generalization occurs when a new situation is perceived as being similar to a past situation based on superficial features, although the two situations are structurally different (Finkelstein and Haleblian, 2002). The perceived similarity triggers the application of routines developed in the past to the new situation which leads to poor performance (Cohen and Bacdayan, 1994; Zander and Kogut, 1995). Research on new product development (Tripsas and Gavetti, 2000; Gavetti, Levinthal, and Rivkin, 2005) and acquisition performance (Haleblian and Finkelstein, 1999; Finkelstein and

Haleblian, 2002; Ellis *et al.*, 2011) show that while firms benefit from structurally similar experience, they typically fail to recognize the structural differences between prior and subsequent situations and are prone to erroneously generalize their experience.

The rationale behind the transfer of alliance experience to subsequent acquisition performance is that the two organizational activities share significant similarities in their strategic objectives as well as in their implementation (Zollo and Reuer, 2010). Both acquisitions and alliances are extensively used by firms to access and utilize external knowledge (Porrini, 2004; Colombo *et al.*, 2006; Haleblian *et al.*, 2009; Hagedoorn and Wang, 2012), and are similar in their planning, negotiation and execution stages (Zollo and Reuer, 2010). One area in which the similarity between alliances and acquisitions is particularly salient is integration because both alliances and acquisitions require some level of integration between the resources and activities of two distinct organizational entities for value creation (Porrini, 2004; Zollo and Reuer, 2010). Because the routines related to the management of both alliances and acquisitions are mostly developed at the corporate level where these activities are managed (Zollo and Reuer, 2010), it is plausible that firms will perceive alliances and acquisitions as similar activities in terms of integration and apply the routines which they developed in their past alliances, to subsequent acquisitions.

Although empirical evidence supports this intuition, the findings on performance implications of transferring integration routines from alliances to acquisitions remain inconclusive. Porrini (2004) for example argues that alliances improve firms' ability to manage resource integration and finds a U-shaped relationship between acquirers' alliance experience and abnormal stock returns in domestic U.S. acquisitions. Zollo and Reuer (2010) however find evidence from survey data on alliances and acquisitions of U.S. banks that alliance experience affects acquirers' abnormal stock returns and accounting measures of performance positively when the level of integration following an acquisition is low and negatively when it is high.

While the studies of Porrini (2004) and Zollo and Reuer (2010) provide valuable insights, they offer conflicting arguments as to how alliance experience affects firms' integration capabilities and performance in their acquisitions. Specifically, while the former suggests that alliance experience enhances integration in subsequent acquisitions, the latter argues that alliances are unlikely to provide such benefits. We suggest that these conflicting arguments result from the authors' treatment of alliance experience as a homogenous construct, *i.e.* the assumption that all alliances comprising a firm's alliance experience are characterized by a similar degree of integration between alliance partners. Focusing on technological knowledge, which is an important resource firms seek to utilize through alliances and acquisitions (*e.g.* Cassiman and Veugelers, 2006; Colombo *et al.*, 2006; Makri *et al.*, 2010; Hagedoorn and Wang, 2012), we argue that alliances, like acquisitions, differ in their degree and nature of integration, depending on the knowledge utilization goals of the partnering firms. Drawing on transfer theory, we suggest that to the extent the knowledge utilization goals in a firm's alliances and acquisitions are congruent, the integration processes in the former and in the latter are structurally similar and the application of routines developed in alliances to acquisitions will enhance performance. We further argue that when these goals are incongruent, erroneous generalization of routines developed in alliances will undermine performance in acquisitions. We discuss below different knowledge utilization goals in alliances and the transfer of routines developed in alliances to subsequent acquisitions.

Knowledge utilization in alliances

While alliances are formed to undertake a wide variety of tasks, an important motivation for firms to join alliances is to utilize their alliance partners' technological knowledge, particularly in high-technology settings (*e.g.* Mowery *et al.*, 1996; Hoang and Rothaermel, 2010). Research on alliances distinguishes two strategies that firms can pursue to realize this goal: *knowledge acquisition* and *knowledge access without acquisition* (Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Mowery *et al.*, 2002; Grant and Baden-Fuller, 2004). Firms pursuing a knowledge acquisition strategy seek to internalize their alliance partners' knowledge through organizational learning (*e.g.* Inkpen, 1998; Inkpen and Tsang, 2007). Such alliances are defined as KA alliances (Mowery *et al.*, 1996, 2002). In contrast, alliances characterized by knowledge access without acquisition are formed by firms which seek CS rather than knowledge transfer. In CS alliances partnering firms focus their capability development efforts to specialize each in their distinct but complementary areas of expertise, rather than to replicate each other's capabilities (Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Mowery *et al.*, 2002; Grant and Baden-Fuller, 2004; Lui, 2009). KA and CS alliances require different knowledge utilization mechanisms due to their distinct knowledge utilization goals (Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Mowery *et al.*, 2002).

Knowledge acquisition alliances and acquisition performance

As the knowledge utilization goal in KA alliances is to internalize the alliance partners' knowledge, these alliances are characterized by a high degree of knowledge integration. In fact, the success of KA alliances are determined by the extent to which alliance partners integrate each other's knowledge into their own knowledge bases (Mowery *et al.*, 1996). Although alliances provide partner firms with access to each other's capabilities and know-how (Kale *et al.*, 2002), alliance participation is not enough to realize interpartner learning. Important preconditions for such learning are the intent and effort to learn (Inkpen and Tsang, 2007). In their study on alliances between Asian and Western partners Hamel, Doz and Prahalad (1989 p. 134) note that "*in every case in which a Japanese company emerged from an alliance stronger than its Western partner, the Japanese company had made a greater effort to learn*". To successfully learn from their alliance partners and acquire their knowledge, it is essential that firms act upon their learning intent by incorporating knowledge transfer mechanisms into the design of their alliances (Mowery *et al.*, 2002), and devise internal processes to facilitate the internal application of the transferred knowledge (Inkpen and Dinur, 1998).

An illustrative case for knowledge acquisition through learning from alliance partners is the NUMMI alliance between General Motors (GM) and Toyota formed in 1983 to jointly operate a production facility in the US (Inkpen, 2008). GM's intention to learn Toyota's manufacturing techniques was explicitly reflected in the alliance agreement which included provisions for knowledge transfer such as site visits of GM personnel (Mowery *et al.*, 2002). These site visits provided valuable exposure for GM to Toyota's production capabilities because a significant portion of knowledge underlying firm capabilities is tacit (Dyer and Singh, 1998) and can only be transferred by interactions of alliance partners' personnel at the operating level (Inkpen and Dinur, 1998; Janowicz-Panjaitan and Noorderhaven, 2009). While such interactions allowed GM personnel to individually learn about Toyota's production techniques, GM adopted further measures to manage these individual learning experiences. Such measures included setting up a Technical Liaison Office to coordinate the site visits, setting explicit learning goals for visiting personnel, systematically planning their reentry into GM and requiring them to codify learning experiences (Inkpen, 2008). Through these systematical learning efforts, GM was able to facilitate the diffusion and application of Toyota production techniques in its other plants and to achieve significant reductions in production costs (Inkpen, 2008).

As the GM case illustrates, knowledge transfer and integration from alliance partners requires firms to set up such mechanisms that allow observation of how an alliance partner applies its knowledge at the operating level, codification of lessons drawn from these observations, and diffusion of these lessons within the firm. As firms accumulate experience in KA alliances, these knowledge utilization mechanisms are stored in knowledge utilization routines (Cohen and Bacdayan, 1994) which collectively lead to a knowledge acquisition capability (Zollo and Winter, 2002). The routinized application of this capability does not only allow a firm to efficiently integrate its alliance partners' knowledge in subsequent KA alliances, it can also enhance knowledge integration in its subsequent acquisitions, depending on the knowledge integration requirements in such acquisitions.

An important factor determining the knowledge integration requirements in an acquisition is the interdependence between the acquirer and target firms in terms of technological knowledge (Puranam and Srikanth, 2007; Puranam, Singh, and Chaudhuri, 2009). Such interdependence is high in industries in which commercial products are typically developed based on multiple technological components whose ownership rights are distributed across multiple firms in the industry. This is for instance the case in the semiconductor industry (Levin *et al.*, 1987; Merges and Nelson, 1990; Ziedonis, 2004). The relationship between commercial products and components of technological knowledge in such industries is referred to as "complex" because of the multiple links between the former and the latter (Levin *et al.*, 1987; Merges and Nelson, 1990). Acquisitions can be effective tools for firms in industries with complex technologies to reduce their dependence on their rivals' technologies. Indeed, semiconductor firms widely use acquisitions for technological knowledge sourcing (Phene, Tallman, and Almeida, 2010; Wagner, 2011). In these acquisitions the integration of the target firm`s technological knowledge into the acquirer firm`s operations following an acquisition is desirable because this knowledge is likely to be utilized in the development of new products by the acquirer firm (Puranam and Srikanth, 2007). This process is structurally similar to the knowledge acquisition process in KA alliances as both processes share the same objective, which is integrating external knowledge into the internal knowledge base. Thus, the knowledge acquisition capability developed in KA alliances may enhance knowledge integration and performance in acquisitions in semiconductor industry.

Hypothesis 1a: KA alliance experience is positively associated with acquisition performance in the semiconductor industry.

In contrast to industries with complex technologies, the technological knowledge interdependence between firms is low in industries with `discrete technologies`, which are defined as technological settings in which commercial products are developed based on relatively few "purpose-built" technological innovations which are either weakly related or unrelated to other products (Levin *et al.*, 1987; Merges and Nelson, 1990). In the pharmaceutical industry for example, most acquisitions are made by larger pharmaceutical firms to internalize the product development projects or unique capabilities, such as generation of innovative ideas, of smaller biotechnology firms (Pisano, 2006). In these acquisitions a large-scale integration of the target firm's technological knowledge into the acquiring firm's operations is unlikely to be beneficial because in most cases such knowledge has been created for the development of a specific product and is unlikely to be utilized in other product development projects (Reitzig, 2004).

Since the target firm's operations are likely to be continued as a separate business unit (Puranam and Srikanth, 2007), the knowledge utilization goal in these acquisitions is the exploitation of complementarities between the acquirer and target firms' distinct knowledge bases, rather than their integration. This process is structurally different than the knowledge acquisition process in KA alliances. Thus, the application of knowledge acquisition routines developed in KA alliances may impede acquisition performance for at least two reasons. First, the application of these routines may lead the acquiring firm to direct its managerial attention to knowledge integration and prevent the recognition of distinct competences of the acquirer and target firms' knowledge bases. Second, the emphasis on knowledge integration in acquisition management may interfere with the target firm's organizational processes and may disrupt the further development of the target firm's technology.

Hypothesis 1b: KA alliance experience is negatively associated with acquisition performance in the pharmaceutical industry.

Complementary specialization alliances and acquisition performance

In contrast to KA alliances which facilitate knowledge transfer between alliance partners, CS alliances allow partnering firms to pool their complementary capabilities, and jointly apply them to commercial outcomes (Mowery *et al.*, 2002; Grant and Baden-Fuller, 2004). CS alliances provide significant efficiency gains as they allow partnering firms to simultaneously specialize in their own areas of expertise and utilize each other's complementary capabilities (Nakamura *et al.*, 1996). A typical example is the alliance between Daimler and SMH (the producer of Swatch watches) who jointly designed and produced the “Smart” car. Its “out-of-the-box” design and lightweight body are the result of the design capabilities of SMH (Hård and Knie, 2001), while its adequate mechanical features despite the size limitations are the result of Daimler’s expertise in automotive engineering. Despite their success in developing the Smart car, neither of the two firms has actively tried to internalize each other’s capabilities for competitive reasons (Grant and Baden-Fuller, 2004).

Differences in knowledge utilization in KA and CS alliances are reflected in their design and execution. While formal provisions for knowledge exchange between alliance partners are essential in the design of KA alliances, they are absent in CS alliances (Mowery *et al.*, 2002). Within the framework of these knowledge exchange provisions, the partnering firms in KA alliances have a considerable control over the knowledge utilization process, as they can create and implement mechanisms to facilitate the transfer and internal application of their alliance partners’ knowledge, as illustrated by GM-Toyota alliance. In CS alliances, however, the knowledge utilization process requires that each alliance partner individually applies its knowledge toward a joint outcome. In the absence of formal knowledge exchange provisions, firms rely on informal coordination mechanisms such as trust to ensure the contribution of their alliance partners to the desired alliance outcome (Lui, 2009). Such trust is the result of the confidence that an alliance partner does not only has the technological knowledge to carry out its part of the division of labor in the alliance, but it also will apply this knowledge in the way specified at the outset of the alliance. Building this confidence requires that alliance partners recognize each other’s respective complementary competences, and develop a framework to combine them towards a joint outcome. As firms accumulate experience in CS alliances, the ability to recognize and combine complementarities between distinct technological knowledge bases is stored in organizational routines, leading to a knowledge combination capability.

While the routinized application of this capability allows firms to effectively execute subsequent CS alliances, it can also be beneficial in acquisitions. Since most acquisitions in pharmaceutical industry are likely to be motivated by the potential exploitation of the complementarities between the acquirer and target firms, as we argued above, managing these acquisitions is structurally similar to the knowledge combination process in CS alliances. The application of the knowledge combination capability developed in CS alliances can thus enhance performance in these acquisitions, by allowing the acquirer firms to leverage the complementarities between their knowledge bases and those of the target firms while keeping them distinct.

Hypothesis 2a: CS alliance experience is positively associated with acquisition performance in the pharmaceutical industry.

While CS alliances improve knowledge combination capabilities, they teach firms little about knowledge integration. The lack of knowledge exchange opportunities with alliance partners, which may be explicitly restricted in the alliance agreements (Mowery *et al.*, 2002), and the emphasis on knowledge access and combination rather than acquisition and integration, prevents firms from developing knowledge integration routines by participating in CS alliances. The application of knowledge combination routines developed in CS alliances can impede performance in acquisitions motivated by resource integration, such as acquisitions in semiconductor industry, as they neglect the intensive interaction processes for knowledge acquisition, and are unlikely to facilitate the necessary degree of knowledge integration.

Hypothesis 2b: CS alliance experience is negatively associated with acquisition performance in the semiconductor industry.

Moderating effects of internal R&D

Thus far we have argued that alliance experience positively affects acquisition performance when knowledge utilization processes across alliances and acquisitions are structurally similar, and negatively when they are structurally different. Firms however do not depend only on alliances to develop knowledge utilization capabilities, but also on internal R&D (Hagedoorn and Wang, 2012).

Investment in R&D provides a firm with product-specific knowledge (the knowledge underlying the products based on that R&D), as well as with "generic" knowledge, which can be described as "…*a body of generic understanding about how things work, key variables affecting performance, the nature of major opportunities and currently binding constraints, and promising approaches to pushing these back.*" (Nelson, 1990 p.196). Because generic knowledge "encompasses broad principles or understandings", it deepens a firm's general understanding of technology, and the applications of technology in a wider range of areas than a firm's existing products (Argyres and Silverman, 2004 p.935). Generic knowledge is therefore relatively generalizable, and can endow a firm with the ability to benefit from new and relatively unfamiliar external knowledge. In an acquisition context, generic R&D knowledge can thus enable an acquirer firm to deal with complexities related to linking the target firm's technological knowledge base to its own (Desyllas and Hughes, 2010).

One such complexity pertains to the fit between the acquirer firm's existing knowledge utilization routines and the target firm's target firm's technological operations. We suggest that as a firm's R&D intensity increases, its generic R&D knowledge base expands, allowing the firm to evaluate with greater accuracy how to link a target firm's knowledge base to its own. Although greater R&D intensity may not necessarily lead to a greater generic knowledge base, the widely established association between R&D intensity and a firm's ability to benefit from new and novel external knowledge suggest a strong relationship between them (Cohen and Levinthal, 1990). Furthermore, R&D intensity is shown to positively affect the early adoption of new organizational routines (Massini *et al.*, 2002), suggesting that greater R&D intensity decreases the rigidity of firms' routines, thus making them less likely to be semi-automatically transferred to new situations. We therefore expect firms with greater degrees of R&D intensity to have a more accurate judgment on the applicability of knowledge utilization routines developed in alliances to subsequent acquisitions which can prevent firms from erroneously generalizing them.

Hypothesis 3a: The negative relationship between KA alliance experience and acquisition performance in the pharmaceutical industry is mitigated by the intensity of internal R&D.

Hypothesis 3b: The negative relationship between CS alliance experience and acquisition performance in the semiconductor industry is mitigated by the intensity of internal R&D.

METHODOLOGY

Sample and data sources

We test our hypotheses on a sample of 316 acquisitions in two high technology industries, namely semiconductors and pharmaceuticals[10]. Several reasons motivated our focus on these two industries. First, semiconductors and pharmaceuticals are typical examples for complex and discrete technologies, respectively (Levin *et al.*, 1987; Cohen *et al.*, 2000), hence provide a suitable empirical context to test our hypotheses. Second, technology plays a vital role for both industries as firms in both industries actively patent (Sorensen and Stuart, 2000). Third, external technological knowledge utilization through alliances and acquisitions is common in both industries: According to the SDC Acquisition and Alliance databases, 11 percent of all acquisitions between 1996 and 2002 are made by semiconductor or pharmaceutical firms, while 24 percent of alliances formed by patent-holding firms between 1991 and 2001 involve firms from these industries.

To construct our sample we identify completed acquisitions leading to 100 percent ownership in the *SDC Acquisitions Database* with announcement dates between 1996 and 2002 (inclusive) by semiconductor and pharmaceutical firms which have at least one alliance in the *SDC Alliance Database* with a patent-holding partner at the ultimate parent level[11] in five years preceding a focal acquisition. This initial search resulted in 352 acquisitions. We then obtain patent data from NBER patent data project (Hall *et al.*, 2001) for the acquiring firms in our sample and for their alliance partners, to determine the knowledge utilization strategies

[10] Semiconductor and pharmaceutical industries are represented by SIC codes 3674 and 2834 respectively.
[11] We exclude alliance among subsidiaries to eliminate concerns associated with diffusion of technological knowledge within corporate structures.

materialized in the acquiring firms' alliances and to construct our independent variables. Finally we obtain stock price data for acquiring firms from the *CRSP Database* to construct our dependent variable, and financial data from *Compustat Database* to construct our control variables. We exclude 30 acquisitions due to missing stock price and financial data, and six acquisitions due to their outlier status with respect to the dependent variable[12]. Our final sample includes 316 acquisitions of which 219 are realized by 52 semiconductor firms and 97 are realized by 29 pharmaceutical firms.

Dependent variable

We use the standard event study methodology (Brown and Warner, 1985) to measure our dependent variable acquisition performance with cumulative abnormal returns (CAR) associated with an acquisition announcement. CARs represent unanticipated returns to a stock resulting from a certain event, in this case an acquisition. Event study methodology is commonly used in both management and finance research (Haleblian *et al.*, 2009), and several studies show that CARs correlate with other measures of post-acquisition performance (*e.g.* Healy, Palepu, and Ruback, 1992; Kaplan and Weisbach, 1992). To calculate CARs we first estimate the following asset pricing model using historical data from a 240-day period preceding an acquisition announcement (Anand and Khanna, 2000):

$$r_{it} = \alpha_i + \beta r_{mt} + \varepsilon_{it}$$

Here r_{it} denotes returns for firm *i* on day *t*, r_{mt} denotes corresponding daily returns on CRSP value weighted index and ε_{it} is distributed i.i.d. We then use the estimates from the asset pricing model

[12] Among 322 acquisitions with complete data, three acquisitions in semiconductor and three in pharmaceutical industries have dependent variables which are more than three standard deviations away from the mean. We exclude these cases from our analyses to prevent our results from being influenced by outliers.

to calculate predicted returns over a five day period around the acquisition announcement date (-2, 2) *i.e.* the "event window". Using a short event window mitigates the risk of including confounding events within the event window (McWilliams and Siegel, 1997). Next, we calculate abnormal returns within the event window by subtracting the predicted returns from the actual returns. Finally we calculate CARs as the summation of abnormal returns within the event window.

Independent variables

Our independent variables are acquiring firms' experience in KA and CS alliances. To construct these variables we first identify all alliances of acquiring firms in our sample with patent-holding partners in five years preceding a focal acquisition year. Using a five year window to measure the effects of an alliance is consistent with prior research in this area (Kale *et al.*, 2002; Heimeriks and Duysters, 2007). We then analyze the development of acquiring firms' technological profiles with respect to technological profiles of their alliance partners by measuring the technological distance between them one year before and five years after the alliance formation year. Consistent with prior research (*e.g.* Vasudeva and Anand, 2011), we measure technological distance between alliance partners using the technological similarity measure developed by Jaffe (1986) based on uncentered correlation between patent portfolios of alliance partners and calculated with the following formula:

$$P_{ij} = F_i F`_j / [(F_i F_j)(F_{ji})]^{1/2}$$

where P_{ij} is the technological similarity between two patent portfolios, F_i is the vector of technological capabilities for firm *i*, and F_j is the vector of technological capabilities for firm *j*. The vector *F* is represented by (F_1, F_2, F_3....F_k) where F_k is the number of patents in NBER patent class *k.* This similarity measure ranges from 0 to 1 such that 0 represents complete dissimilarity and 1 represents perfect similarity between alliance partners' technological profiles. To calculate the technological distance, we subtract the similarity values from 1. Decreasing technological distance after the alliance formation signifies convergence between partners' technological capabilities and is an indicator of knowledge spillovers (Jaffe, 1986) and learning (Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Mowery *et al.*, 2002). Consequently, alliances in which the technological distance between partners' patent portfolios decreased after the alliance formation are classified as KA alliances.

While increasing technological distance between alliance partners can indicate CS (Mowery *et al.*, 2002), we perform an additional analysis to evaluate whether the increase in technological distance unfolds in a complementary rather than random way. Following Makri, Hitt and Lane (2010) we measure complementarity between alliance partners` technological profiles by their patents in the same patent subcategories but in different patent classes. The US Patent Office classifies patents in 417 3-digit classes and Hall, Jaffe and Trajtenberg (2001) further aggregate these 417 classes into 37 subcategories and 6 main categories in the NBER Patent Data Project (Hall *et al.*, 2001). Each class belongs to only one subcategory. We measure the degree of complementarity by the ratio of alliance partners' successful patent applications in the same patent subcategory but in different patent classes, to their all successful patent applications. For each alliance we compute the degree of complementarity before and five years after the alliance formation year. We then identify alliances in which both technological distance and complementarity between partner firms increase after the alliance formation as CS alliances. We include all alliances which are not classified as either KA or CS type in the residual `other` category.

After classifying the alliances of acquiring firms into KA and CS categories, we compute the variables *Acquirer KA alliance experience* and *Acquirer CS alliance experience* for each acquiring firm as the ratios of each firm's KA and CS alliances to its all alliances, respectively. Calculating KA and CS alliance experience as a ratio of alliance experience rather than as absolute count values helps us focus on the importance of a particular external knowledge utilization strategy in an acquiring firm's technology sourcing efforts, and facilitates comparisons between firms with numerous alliances and those with relatively few.

Control variables

We include several control variables to exclude alternative explanations for our results. First, we control for acquiring firms' total alliance experience in five years preceding the acquisition announcement year to account for any influence on acquisition performance arising from general alliance experience (Porrini, 2004; Zollo and Reuer, 2010). We also control for acquiring firms' acquisition experience in five years preceding the acquisition announcement year and for the natural logarithm of acquiring firms' total assets as of one year before the acquisition year, since both acquisition experience and firm size are well recognized for their influence on acquisition performance (Haleblian *et al.*, 2009). Further, we control for the acquiring firms' average R&D intensity and average return on assets (ROA) in five years preceding the acquisition year as these variables affect acquirers' ability to convert the acquired knowledge into innovative performance (Makri *et al.*, 2010) ,which in turn can affect the stock market response to an acquisition. We further control for industry relatedness between acquirer and targets firms with a dummy variable which is coded as 1 when acquirer and target firms are in the same 4-digit SIC code. We also include year dummies to control for unobserved heterogeneity associated with acquisition years in our sample (Schijven and Hitt, 2012). We also control for the market value of the acquirer firms to account for the possible influence of acquiring firms' market capitalization on the market's response to the acquisition.

We further control in our analysis for the relative weights of exploration and exploitation in acquirer firms' knowledge stock as of one year before the acquisition year, to account for the possible influence of acquiring firms' tendencies towards exploratory and exploitative capability development (March, 1991). Following Nooteboom *et al* (2007), we classify acquirer firm patents as *exploratory* if a focal patent is in a patent class in which the acquiring firm has not successfully applied for a patent in five years preceding the application year of the focal patent, and as *exploitative* if a focal patent is in a patent class in which the acquiring firm has successfully applied for a patent in five years preceding the application year of the focal patent. We then calculate *Acquirer R&D exploration ratio* for each acquirer firm by dividing the number of exploratory patents by the total number of successfully applied patents as of each acquisition year.

Empirical analysis

To account for unobserved heterogeneity among acquiring firms we use a fixed effects estimation with robust standard errors, and cluster standard errors on unique acquirers in our sample to avoid overestimating the significance levels of coefficients (Schijven and Hitt, 2012). We estimate our models separately on semiconductor and pharmaceutical samples which prevents the results from being influenced by cross-industry variation (Sorensen and Stuart, 2000).

RESULTS

Descriptive statistics

Descriptive statistics and pairwise correlations of the variables for semiconductor and pharmaceutical samples are reported in Tables 1 and 2 respectively. The mean CAR over the five-day window is -0.242 percent in the semiconductor sample and -0.377 percent in the pharmaceutical sample. The proportion of positive returns is 49 percent in the semiconductor sample and 42 percent in the pharmaceutical sample. In the semiconductor sample correlations between *Acquirer alliance experience*, *Acquirer acquisition experience*, *Acquirer total assets, Acquirer average ROA* and *Stock market value* are high, suggesting that large semiconductor firms tend to have a higher ROA, and engage in acquisitions and alliances more than smaller firms. In the pharmaceutical sample correlations between *Acquirer total assets, Acquirer alliance experience, Acquirer acquisition experience, Acquirer average ROA*, *Acquirer average R&D intensity* and *Stock market value* are high suggesting that larger pharmaceutical firms tend to engage in more acquisitions and alliances, and that returns to assets are invested into R&D. While these high correlations are not surprising given the characteristics of these industries, they may present a collinearity problem in regression models. To check whether our empirical models are affected by multicollinearity among predictor variables, we examine the variance inflation factors (VIF) of our variables separately for both samples. In the semiconductor sample the variable with the highest VIF is *Acquirer alliance experience* (5.22) with a sample mean VIF 2.78, and in the pharmaceutical sample it is *Acquirer total assets* (8.42) with a sample mean VIF 3.20. Since these values are below the commonly accepted threshold value of 10 (Studenmund, 2010), we conclude that multicollinearity does not pose a significant problem in our analyses.

Table 1 – Descriptive statistics and pairwise correlations for the semiconductor sample

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) CAR(-2, 2)	-0.002	0.086	-0.234	0.274	1.00										
(2) Acquirer KA alliance experience	0.661	0.295	0.000	1.000	0.11	1.00									
(3) Acquirer CS alliance experience	0.114	0.211	0.000	1.000	-0.03	-0.51	1.00								
(4) Acquirer alliance experience	12.379	16.561	1.000	49.000	0.02	0.14	-0.10	1.00							
(5) Acquirer acquisition experience	5.703	6.746	0.000	34.000	-0.01	0.18	-0.19	0.59	1.00						
(6) LN Acquirer total assets	7.576	2.046	2.229	10.778	-0.01	0.11	-0.13	0.75	0.66	1.00					
(7) Acquirer average R&D intensity	0.147	0.081	0.017	0.742	-0.07	-0.25	-0.08	-0.33	0.03	-0.15	1.00				
(8) Acquirer average ROA	0.179	0.116	-0.208	0.390	0.07	0.17	-0.01	0.70	0.40	0.75	-0.46	1.00			
(9) Stock market value	52.318	104.716	0.004	462.520	0.03	0.16	-0.10	0.85	0.59	0.64	-0.25	0.65	1.00		
(10) Acquirer R&D exploration ratio	0.190	0.264	0.000	1.000	0.02	-0.13	0.01	-0.41	-0.36	-0.55	0.19	-0.43	-0.30	1.00	
(11) Industry relatedness	0.397	0.490	0.000	1.000	0.02	-0.04	0.05	-0.17	-0.15	-0.12	0.07	-0.10	-0.13	0.13	1.0

All correlations above 0.14 are significant

Table 2 – Descriptive statistics and pairwise correlations for the pharmaceutical sample

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) CAR(-2, 2)	-0.004	0.054	-0.173	0.151	1.00										
(2) Acquirer KA alliance experience	0.477	0.337	0.000	1.000	0.07	1.00									
(3) Acquirer CS alliance experience	0.166	0.250	0.000	1.000	0.02	-0.31	1.00								
(4) Acquirer alliance experience	6.979	6.479	1.000	21.000	-0.02	0.28	-0.15	1.00							
(5) Acquirer acquisition experience	4.887	4.661	0.000	16.000	-0.06	-0.19	-0.00	0.17	1.00						
(6) LN Acquirer total assets	7.526	2.821	1.430	10.692	-0.09	-0.06	-0.03	0.62	0.69	1.00					
(7) Acquirer average R&D intensity	0.559	1.026	0.019	6.157	0.12	0.22	-0.04	-0.37	-0.42	-0.60	1.00				
(8) Acquirer average ROA	0.088	0.260	-1.089	0.354	-0.01	-0.16	0.01	0.57	0.58	0.82	-0.77	1.00			
(9) Stock market value	52.622	56.897	0.027	198.923	-0.06	-0.00	0.03	0.41	0.73	0.81	-0.41	0.60	1.00		
(10) Acquirer R&D exploration ratio	0.218	0.314	0.000	1.000	0.13	-0.17	0.01	-0.48	-0.24	-0.53	0.11	-0.26	-0.51	1.00	
(11) Industry relatedness	0.443	0.499	0.000	1.000	-0.06	0.07	0.15	-0.03	-0.19	-0.16	0.16	-0.17	-0.15	0.06	1.00

All correlations above 0.22 are significant

Descriptive statistics reveal differences as well as similarities between the semiconductor and pharmaceutical industries. The mean value for Acquirer KA alliance experience is higher in the semiconductor sample but the mean value for Acquirer CS alliance experience is higher in the pharmaceutical sample, supporting our contention that KA alliances are more likely to be formed in industries with complex technologies and CS alliances are more likely to be formed in industries with discrete technologies. While before a focal acquisition average acquirers in both industries have similar amounts of acquisition experience, an average acquirer in the semiconductor sample has experienced almost twice the number of alliances with patent-holding partners than an average acquirer in the pharmaceutical sample, which highlights the strong technological interdependence in the semiconductor industry. In contrast, average R&D intensity is almost four times higher in the pharmaceutical sample confirming the importance of discrete and 'purpose-built' nature of technological knowledge in this industry.

The remarkably higher mean value and lower standard deviation of *Average ROA* for acquirers in the semiconductor sample compared to acquirers in the pharmaceutical sample suggests that while financial profitability in the latter industry is on average relatively low, it is subject to more variation. This observation is consistent with the widely-acknowledged characterization of the pharmaceutical industry as having higher levels of uncertainty than other high technology industries (Pisano, 2006). Acquirers in both samples exhibit similar levels of exploration (as opposed to exploitation) orientation in their R&D efforts, although the variation among firms in the pharmaceutical sample is relatively higher. While in both samples less than half of the acquisitions occurred between firms sharing the same primary 4-digit SIC code, pharmaceutical acquirers exhibit a slightly stronger preference for targets in their own SIC code (44 percent) than semiconductor acquirers (40 percent).

Regression results

Table 3 presents the regression results on the semiconductor sample used to test Hypotheses 1a, 2b and 3b. Models 1 and 2 include control variables, Model 3 adds alliance experience to controls, Model 4 is the full model with the main effects and Model 5 adds the interaction effect between *Acquirer CS alliance experience* and *Acquirer average R&D intensity* to test Hypothesis 3b. Among control variables *Acquirer R&D exploration ratio* is significant across all models suggesting that higher degrees of exploratory R&D leads to a better performance in acquisitions of semiconductor firms. *Acquirer alliance experience* is not significant in Models 3 through 5 which is consistent with prior research on experience spillovers (Zollo and Reuer, 2010).

Hypothesis 1a predicts that KA alliance experience is positively associated with acquisition performance and Hypothesis 2b predicts that CS alliance experience is negatively associated with acquisition performance in the semiconductor industry. The coefficient for *Acquirer KA alliance experience* is positive but insignificant in Model 4 providing no support to H1a. The coefficient for *Acquirer CS alliance experience* is negative and significant supporting H2b. This finding suggests that all else being equal, one standard deviation increase in CS alliance experience decreases acquirer CARs associated with an acquisition by 3.27 percent in the semiconductor industry. In another interpretation, an acquirer firm which followed a strategy toward CS in all of its alliances can be expected to have 15.5 percent lower CARs following a subsequent acquisition than an acquirer firm with no CS alliance experience, all else being equal. Hypothesis 3b predicts that the negative effects of CS alliance experience on acquisition performance are mitigated by R&D intensity. We test H3b with Model 5. The coefficient of the interaction term is positive and significant supporting H3b. This finding suggests that when

Acquirer CS alliance experience and *Acquirer average R&D intensity* are at their means, the predicted CAR is 0.77 percent whereas when *Acquirer CS alliance experience* is held at its mean and *Acquirer average R&D intensity* increases by 1 percent the predicted CAR is 1.44 percent. The graph in Figure 1 illustrates the change in CARs in the semiconductor sample at different levels of *Acquirer CS alliance experience* and *Acquirer average R&D intensity*.

Table 3 – OLS fixed-effects regression models on semiconductor sample

Model	(1)	(2)	(3)	(4)	(5)
Dependent variable	Car(-2,2)	Car(-2,2)	Car(-2,2)	Car(-2,2)	Car(-2,2)
Acquirer KA alliance experience				0.00280	-0.00474
				(0.06083)	(0.06382)
Acquirer CS alliance experience				-0.15508**	-1.03850***
				(0.07618)	(0.30451)
Acquirer CS alliance experience X R&D intensity					7.34906***
					(2.58375)
Acquirer alliance experience			0.00140	0.00040	-0.00003
			(0.00150)	(0.00132)	(0.00141)
Acquirer acquisition experience	-0.00149	-0.00036	-0.00001	-0.00080	-0.00147
	(0.00164)	(0.00252)	(0.00248)	(0.00244)	(0.00245)
LN Acquirer total assets	0.04656	0.09285*	0.09519*	0.08950*	0.09131**
	(0.03469)	(0.04948)	(0.04859)	(0.04855)	(0.04473)
Acquirer average R&D intensity	0.23823	0.53693	0.68712	0.55633	-0.17170
	(0.35280)	(0.71038)	(0.73042)	(0.72185)	(0.76326)
Acquirer average ROA	0.39578	0.24567	0.28234	0.10276	-0.26521
	(0.41094)	(0.33733)	(0.33787)	(0.26435)	(0.29137)
Stock market value	0.00003	0.00007	0.00005	0.00009	0.00009
	(0.00010)	(0.00011)	(0.00011)	(0.00011)	(0.00010)
Acquirer R&D exploration ratio	0.56485***	0.57567***	0.58210***	0.55262***	0.52931***
	(0.12623)	(0.11900)	(0.11873)	(0.12219)	(0.14564)
Industry relatedness	-0.00900	-0.00796	-0.00759	-0.00678	-0.00728
	(0.01040)	(0.01094)	(0.01108)	(0.01124)	(0.01162)
Constant	-0.55759**	-0.87895**	-0.94781**	-0.80969**	-0.64180*
	(0.27542)	(0.39822)	(0.39454)	(0.37713)	(0.37058)
Year dummies	Excluded	Included	Included	Included	Included
Observations	219	219	219	219	219
R-squared	0.07947	0.13046	0.13252	0.14461	0.16979
Prob > F	0.00000	0.00000	0.00000	0.00000	0.00000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses. All significance tests are two-tailed.

Figure 1 – Interaction between CS alliance experience and R&D intensity on semiconductor sample with 95% confidence intervals

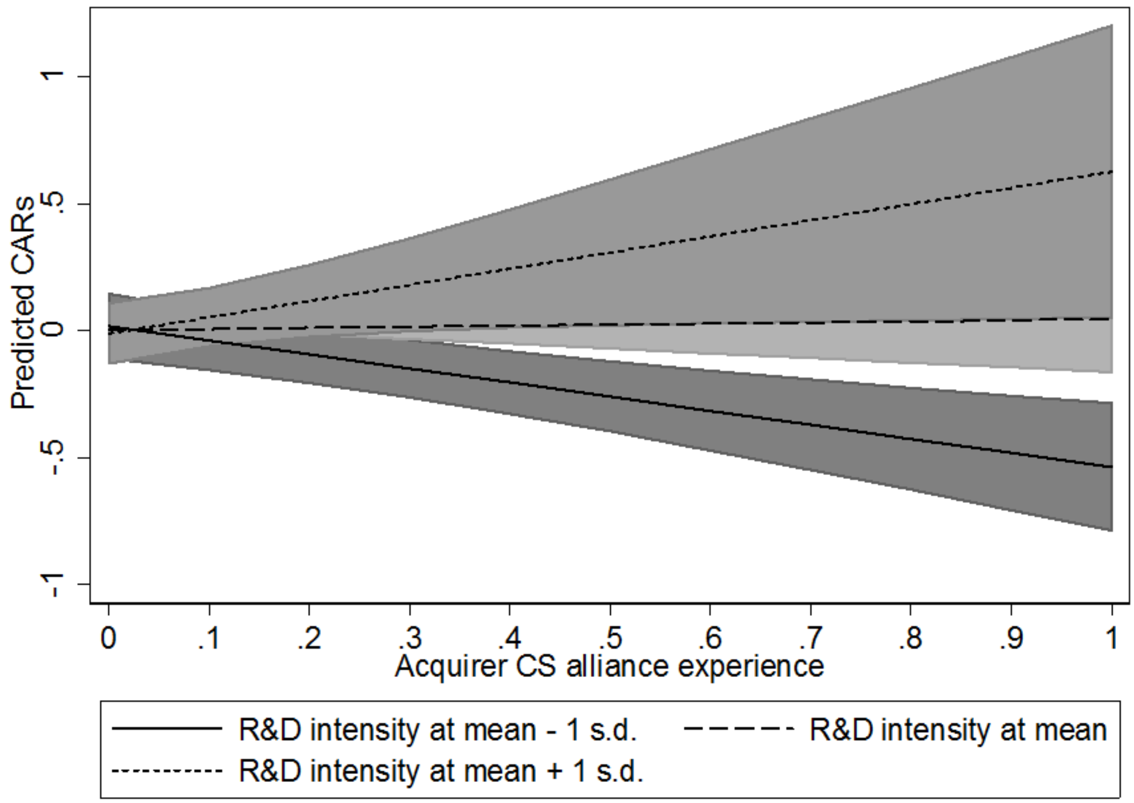


Table 4 presents the regression results on the pharmaceutical sample used to test Hypotheses 1b, 2a and 3a. As in Table 3, Models 6 and 7 are control models, Model 8 is the control model which includes alliance experience, Model 9 is the full model with the main effects and Model 10 adds the interaction effect between *Acquirer KA alliance experience* and *Acquirer average R&D intensity* to test Hypothesis 3a. Similar to the results in the semiconductor sample, in models 8 and 9 the coefficient of alliance experience does not have any statistically significant influence on acquisition performance although it gains marginal significance in model 10.

Table 4 – OLS fixed-effects regression models on pharmaceutical sample

Model	(6)	(7)	(8)	(9)	(10)
Dependent variable	Car(-2,2)	Car(-2,2)	Car(-2,2)	Car(-2,2)	Car(-2,2)
Acquirer KA alliance experience				-0.14687*	-0.16023
				(0.08035)	(0.09941)
Acquirer CS alliance experience				0.07614***	0.08171**
				(0.02138)	(0.03101)
Acquirer KA alliance experience X R&D intensity					0.02364
					(0.09680)
Acquirer alliance experience			0.00054	0.00474	0.00495*
			(0.00274)	(0.00285)	(0.00280)
Acquirer acquisition experience	0.00251**	0.00237	0.00222	0.00282	0.00287
	(0.00101)	(0.00230)	(0.00254)	(0.00194)	(0.00193)
LN Acquirer total assets	-0.00400	1.42e-06	0.00011	0.00580	0.00545
	(0.01524)	(0.02416)	(0.02450)	(0.01979)	(0.02009)
Acquirer average R&D intensity	-0.00059	-0.00538	-0.00482	-0.00274	-0.02477
	(0.01451)	(0.01519)	(0.01644)	(0.01446)	(0.09883)
Acquirer average ROA	0.09019*	0.11044**	0.11026**	0.06345	0.06652
	(0.05130)	(0.05200)	(0.05307)	(0.04752)	(0.04516)
Stock market value	-0.00018	-0.00008	-0.00006	-0.00001	2.45e-07
	(0.00013)	(0.00026)	(0.00030)	(0.00028)	(0.00027)
Acquirer R&D exploration ratio	0.07415	0.10139	0.10149	0.08105	0.08645
	(0.07426)	(0.07677)	(0.07744)	(0.08669)	(0.08591)
Industry relatedness	-0.01534	-0.01240	-0.01254	-0.00219	-0.00247
	(0.00906)	(0.00852)	(0.00856)	(0.00825)	(0.00803)
Constant	0.00637	-0.02459	-0.02912	-0.04258	-0.03375
	(0.11340)	(0.17998)	(0.18775)	(0.15324)	(0.16584)
Year dummies	Excluded	Included	Included	Included	Included
Observations	97	97	97	97	97
R-squared	0.07950	0.13084	0.13127	0.24499	0.24566
Prob > F	0.00080	0.00000	0.00000	0.00000	0.00000

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. All significance tests are two-tailed.

Hypothesis 1b predicts that KA alliance experience is negatively associated with acquisition performance and Hypothesis 2a predicts that CS alliance experience is positively associated with acquisition performance in the pharmaceutical industry. In model 9 the coefficient for *Acquirer KA alliance experience* is negative and significant supporting H1b. This finding suggests that all else being equal, one standard deviation increase in KA alliance experience decreases acquirer CARs associated with an acquisition by 4.95 percent. In another interpretation, an acquirer firm which followed a strategy toward KA from its alliance partners in all of its alliances can be expected to have 14.7 percent lower CARs following a subsequent acquisition than an acquirer firm with no KA alliance experience, all else being equal. The coefficient for *Acquirer CS alliance experience* is positive and significant, supporting H2a. This finding implies that all else being equal, one standard deviation increase in CS alliance experience increases acquirer CARs associated with an acquisition by 1.9 percent in the pharmaceutical industry. Hypothesis 3a predicts that the negative effects of KA alliance experience on acquisition performance are mitigated by R&D intensity. We test H3a with Model 10. The coefficient of the interaction term is negative and insignificant providing no support to H3a. We elaborate on our findings in the following section.

DISCUSSION

In this paper we investigate the transferability of alliance experience to acquisitions from a technological knowledge utilization point of view and find evidence for positive as well as negative transfer. A key contribution of this study is that we develop a theoretical framework based on transfer theory (Ellis, 1965; Cormier and Hagman, 1987) for the transfer of benefits from different types of alliance experience to subsequent acquisitions in high technology settings. This theoretical framework improves our understanding of the determinants of acquisition performance, and allows for a more fine-grained analysis of the effects of alliance experience. Before discussing the theoretical and managerial implications of our findings we want to elaborate on them in more detail.

While we find empirical support for our hypothesized negative transfer effects in both semiconductor and pharmaceutical industries, in the semiconductor industry this is not the case for positive transfer effects. Considering the nature of our dependent variable, this implies that potential benefits of alliance experience in acquisitions by semiconductor firms are not reflected in acquisition performance at the point of acquisition announcement, even though such experience is congruent with the knowledge utilization requirements in this industry. One possible explanation for this is that acquisitions in industries with complex technologies require a greater degree of integration between acquirer and target firms than alliances (Haleblian *et al.*, 2009; Zollo and Reuer, 2010), and the integration of technological knowledge is part of a larger post-acquisition integration process. It is therefore possible that the effects of experience in knowledge integration through alliances are diluted within the overall evaluation of an acquisition and by itself not sufficient enough to generate a positive performance impact.

How can we explain the significant negative effects then? We provide two possible explanations. First, negative transfer resulting from erroneous generalization of past experience materializes easier than positive transfer (Novick, 1988), which requires managerial effort to analyze the similarities between the past and subsequent events and to only apply the past experience when appropriate (Haleblian and Finkelstein, 1999). It is therefore possible that alliance experience that is dissimilar to a focal acquisition in terms of knowledge utilization routines has a stronger impact on acquisition performance than similar alliance experience.

Second, in addition to misapplication of prior knowledge utilization experience, acquiring firms which participate in alliances with knowledge utilization goals incongruent with those required by their subsequent acquisitions may also be neglecting the development of such knowledge utilization routines that are necessary to successfully undertake acquisitions. In the semiconductor industry for example a firm with many CS alliances may be underemphasizing internal knowledge creation. The compensating effect of internal R&D in the semiconductor sample supports this reasoning. In pharmaceuticals, the level of post-acquisition integration is relatively low and acquisition targets are likely to become a separate business unit of acquirer firms rather than that their technological knowledge base is fully integrated. An acquirer with many KA alliances may therefore be overemphasizing knowledge integration, which may negatively impact performance in acquisitions geared to knowledge access.

Contributions to the literature

We make two important contributions to the literature. First, we contribute to the literature on experience spillovers. While our findings are consistent with those of Zollo and Reuer (2010), we refine their findings by unpacking alliance experience and showing that KA and CS alliances differ in terms of knowledge integration. For example while Zollo and Reuer (2010) suggest that alliance experience positively affects performance in acquisitions with a low degree of integration, our findings show that experience in KA alliances affect performance negatively in acquisitions in discrete industries despite the low degree of integration. We therefore show the importance of the type and nature of the alliance experience in analyzing experience spillovers. Similarly, while we concur with Porrini (2004) that alliance experience is particularly beneficial in high technology industries, our analysis shows that there are structural differences across different high technology settings in terms of linkages between components of technological knowledge and commercial products and that acquirers do not benefit from prior alliances with structurally dissimilar knowledge utilization goals to those required in their acquisitions.

We also contribute to the literature on acquisition performance by analyzing the performance implications of experience transfers from a knowledge utilization perspective (Barkema and Schijven, 2008). Specifically, we improve the understanding of positive as well as negative experience transfers (Haleblian and Finkelstein, 1999; Barkema and Schijven, 2008; Zollo and Reuer, 2010) by showing that differences between knowledge utilization goals in past and subsequent events through their effects on organizational routines can influence experience transfers. While the majority of acquisitions fail in terms of *ex-post* performance (Haleblian *et al.*, 2009), our findings suggest that poor performance can be avoided, at least in part, by taking the congruence in terms of knowledge utilization between acquisitions and other corporate development activities such as alliances into account.

Limitations and future research

Like many empirical studies this paper has some limitations that could be addressed by future research. First, by using cumulative abnormal returns as dependent variable we rely on the investors' response to measure acquisition performance. Although this is a widely used approach to measure acquisition performance (*e.g.* Finkelstein and Haleblian, 2002; Uhlenbruck, Hitt, and Semadeni, 2006; Schijven and Hitt, 2012) and literature suggests that cumulative abnormal returns correlate with other post-acquisition performance measures (*e.g.* Healy *et al.*, 1992; Kaplan and Weisbach, 1992), measuring experience transfer effects, which may unfold gradually over time, with the market response to the acquisition announcement may be a limitation. Future research might use other post-acquisition performance measures to complement our analyses.

Second, we rely on the change in alliance partners' patent portfolios to determine the technological knowledge utilization strategies in alliances. While patents are widely acknowledged to represent a firm's technological capabilities (*e.g.* Mowery *et al.*, 1996; Colombo *et al.*, 2006; Nooteboom *et al.*, 2007; Hoang and Rothaermel, 2010; Vasudeva and Anand, 2011) they are *ex-post* measures of technological capability development. Thus in an alliance context measurement of technological capability development with the change in patent portfolios requires the assumption that patenting activity after the alliance formation is in line with the strategic goals of the alliance. Although there is strong support for this assumption in the literature (*e.g.* Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Colombo, 2003; Colombo *et al.*, 2006) future research can supplement patent-based analyses with *ex-ante* measures of alliance strategies to increase the robustness of such analyses.

Our study opens up further opportunities for future research. Although alliance research devotes considerable attention to the role of alliance experience in subsequent alliance performance (*e.g.* Anand and Khanna, 2000; Zollo *et al.*, 2002; Hoang and Rothaermel, 2005; Sampson, 2005), studies on benefits of such experience outside the domain of alliances are surprisingly few. Our study shows that benefits of experience in different types of alliances can have far-reaching consequences beyond the domain of alliances. However, in this study we only analyze the heterogeneity in alliance experience from a knowledge utilization point of view. Future research might continue unpacking alliance experience using different classifications and examine contextual similarities across different corporate development activities.

Managerial implications

The most important managerial implication of our study is that managers should not consider alliance and acquisition strategies in isolation but as parts of a general external knowledge utilization strategy. They should accurately analyze potential positive as well as negative spillovers across these corporate development activities. While managers can use alliances to equip their firms with necessary skills to successfully undertake subsequent acquisitions, they should take into account the knowledge utilization dynamics in their industries when designing their corporate development strategies. Specifically, they should screen their alliance partners and acquisition targets as potential sources of external knowledge and carefully evaluate the applicability of knowledge utilization skills developed through alliances. Our findings suggest that firms failing to do so can be subject to significant decreases in their market returns following acquisitions.

CHAPTER 5

GENERAL CONCLUSION

The increasing importance of accessing and utilizing external knowledge leads firms around the world to engage in greater number of alliances to enhance their competitive positions. A vast and growing body of research examines firms' alliance activities using a diverse range of theoretical lenses to aid firms in their pursuit to create value from their alliances. Nevertheless, failure rates of alliances remain high and the degree to which the insights from scholarly research are reflected to managerial practice remains low. This implies a need for bringing alliance research closer to practice with more fine-grained analyses of alliances using management theories. In this dissertation I aim to take a step in this direction by refining the understanding of how firms can benefit from alliances in their attempts to develop technological as well as managerial capabilities.

Theoretical contributions

By using different theoretical lenses such as organizational learning, transfer theory and performance feedback theory this thesis improves our current understanding of how firms can benefit from alliances to develop capabilities. The three studies in this dissertation make several contributions to the literature. In Chapter 2 I examine how firms alter their configuration of their alliance portfolios as a result of performance feedback. Consistent with performance feedback theory (Cyert and March, 1963), I show that firms respond to poor performance by changing their alliance partners but remaining within the existing technological scope of their alliance portfolios, and to good performance by expanding the technological scope of their alliance portfolios with their existing partners. I thus contribute to alliance portfolio literature (*e.g.* Parise and Casher, 2003; Hoffmann, 2007; Wassmer, 2010) by providing a theoretical explanation as well as empirical evidence as to why alliance portfolios evolve in the way they do.

In addition to providing a behavioral explanation of alliance portfolio evolution, my analysis also refines the relationship between performance feedback and risk taking. While the literature suggests that firms' inclination for risk taking increases as their performance diverges from aspiration levels (Cyert and March, 1963), insights on the type and nature of risk taking depending on whether the performance is above or below aspirations are limited. My findings contribute to performance feedback theory by showing that firms assume different types of risk when they perform below and above their aspirations, and that the type of risk taking depends on firms' perceptions as to the causes of poor or good performance.

In Chapter 3, I examine how technological overlap and alliance experience, factors commonly acknowledged as important antecedents of external knowledge utilization, impact complementary specialization, in comparison to knowledge acquisition, as a knowledge utilization outcome in alliances. I show that these factors have different effects on complementary specialization and knowledge acquisition because they improve different sets of a firm's knowledge utilization skills. I thus contribute to the literature by exploring the antecedents of alternative knowledge utilization outcomes in alliances (Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Lubatkin *et al.*, 2001; Mowery *et al.*, 2002; Grant and Baden-Fuller, 2004).

Traditionally, from an organizational learning point of view, alliances are viewed as conduits for interpartner knowledge transfer (*e.g.* Hamel, 1991; Inkpen and Tsang, 2007; Inkpen, 2008), and alliances in which such transfer does not take place are generally considered as arm's-length relationships with little consequences in terms of organizational learning (*e.g.* Anand and Khanna, 2000). Only a few studies (*e.g.* Lubatkin *et al.*, 2001; Grant and Baden-Fuller, 2004) recognize complementary specialization as an alternative mode of knowledge utilization in alliances, and even fewer studies provide empirical evidence for this type of knowledge utilization (*e.g.* Mowery *et al.*, 2002). My findings confirm the viability of complementary specialization as a knowledge utilization strategy, and extend organizational learning theory to explain alternative forms of knowledge utilization in alliances.

In Chapter 4 I extend the analysis in Chapter 3 by examining how participation in knowledge acquisition and complementary specialization alliances affects firms' capabilities to manage their subsequent acquisitions. I first make a comparative analyses of these two types of alliances in terms of the degree of interaction between partnering firms and argue that knowledge acquisition requires a substantially higher degree of interaction than complementary specialization. Drawing on transfer theory, I then show that the managerial capabilities gained in knowledge acquisition alliances are more relevant to acquisitions requiring a low degree of autonomy whereas the managerial capabilities gained in complementary specialization alliances are more useful in acquisitions requiring a high degree of autonomy. My analysis contributes to the literature on experience spillovers between alliances and acquisitions (Porrini, 2004; Zollo and Reuer, 2010) by showing how different types of alliances in a firm's alliance portfolio affect the performance of its acquisitions

Experience spillovers across different forms of interfirm relationships is an emerging research stream, and studies in this area (Porrini, 2004; Zollo and Reuer, 2010) thus far focus on identifying acquisition contexts that are similar to alliances in general. My analysis is novel in that it points at the heterogeneity among a firm's alliances in terms of management practices as well as the consequences of this heterogeneity for the performance of the firm's acquisitions. By doing so, my analysis provides a more precise application of transfer theory than current research to explain experience spillovers across alliances and acquisitions. My findings also show that the experiences gained though different types of alliances can have consequences that extend beyond the domain of alliances. This underscores the importance of evaluating the consequences of alliances to firms' capability development not only at individual alliance level, but also at the alliance portfolio level.

Besides their individual contributions to their respective research streams, the three chapters collectively have two broad implications for research on alliances. First, my findings underscore that knowledge utilization in alliances is a multifaceted concept (Nakamura *et al.*, 1996; Mowery *et al.*, 2002). While each alliance can enable a firm to acquire knowledge from its partner or to develop new knowledge with its partner through complementary specialization, a firm's collection of alliances, *i.e.* its alliance portfolio, can equip the firm with managerial capabilities to enhance its ability to manage not only future alliances but also acquisitions. At the alliance portfolio level, my findings in Chapter 4 show that firms indeed can learn how to manage future interfirm relationships by joining alliances, but what they precisely learn depends on the composition of their alliance portfolios. At the single alliance level, my findings in Chapter 3 highlight the importance of refining the relationship between antecedents of knowledge utilization and its different outcomes, and identifying the relevant antecedents for the intended knowledge utilization goals in an alliance. Together, Chapters 3 and 4 demonstrate how and what firms learn in different types of alliances, and illustrate the need to conduct more fine-grained analyses of organization learning in alliances.

Second, the transfer of experience from a firm's alliances to its acquisitions that I demonstrate in Chapter 4 shows that the consequences of each alliance can extend beyond that particular alliance and collectively a firm's collection of alliances can comprise a strategic asset that can equip the firm with valuable managerial capabilities. I therefore concur with the existing literature that firms can enhance their competitiveness by considering their alliances as a portfolio (Kale and Singh, 2009). However, many firms fail to manage their alliances as such, and my analysis in Chapter 2 provides a possible explanation to this paradox. My findings show that alliance formation decisions are not always made rationally within an overall strategic framework, but guided by other considerations such as short term performance problems or cognitive biases. While a firm's alliance decisions resulting from performance feedback are not necessarily misaligned with its strategic objectives, combined with the observation that the majority of firms do not view their alliances as a coherent portfolio (Kale and Singh, 2009), my findings suggest that in a substantial number of cases such alignment is not achieved. My analyses thus illustrate the need to better understand the circumstances under which managers make alliance decisions, and to reflect this understanding into theory development on alliance portfolios. My findings also demonstrate the usefulness of behavioral approaches in explaining firm heterogeneity in the absence of rationality assumption (Powell *et al.*, 2011).

Managerial implications

The findings of this dissertation have profound implications for managers in shaping their corporate development efforts through interfirm relationships. First, managers should not assume that merely forming alliances would allow them to benefit from their partners' knowledge and capabilities. Rather, they should determine the knowledge utilization strategies they seek to implement in their alliances and equip their firms with necessary absorptive capacity.

Specifically, to enhance their ability to acquire knowledge from alliance partners, managers should build sufficient experience in collaborating with external knowledge sources. To improve their skills to simultaneously exploit the existing technological capabilities of their firms while utilizing the knowledge of their alliance partners, they should screen their potential alliance partners in terms of technological overlap and ensure that sufficient overlap exists.

Second, managers should not consider their alliances in isolation but as elements of their overall portfolio of interfirm relationships to unlock the potential benefits of their alliances. To leverage their experience in alliances to better manage their acquisitions, they should evaluate the autonomy requirements of their acquisitions and assess the extent to which these requirements are compatible with the knowledge utilization practices they apply in their alliances. If there is high compatibility, they should devise such mechanisms that enable the transfer of management practices from alliances to acquisitions, for example by facilitating knowledge exchange between their firms' functions involved in the management of alliances and acquisitions. However, such compatibility may not always exist. In these cases, managers should be wary about transferring the management practices from their alliances to their acquisitions and take precautions to prevent the automatic transfer of inappropriate management routines.

Finally, managers should be aware that alliance formation decisions have broader consequences for their firms that extend beyond the single alliance level. More specifically, while alliances with novel partners can be a feasible solution to address performance problems in some cases, they can alienate a firm's existing alliance partners and negatively impact the overall value the firm derives from its alliance portfolio. Similarly, although performance above aspiration levels can implicitly confirm a firm's choice of alliance partners and provide incentives to form new collaborations with them, it can also prevent the firm from benefiting from novel external knowledge sources. Although performance feedback provides managers an intuitive heuristic to adjust the amount and type of risk they take in their alliance formation decisions, they should also take into account the broader, portfolio-level consequences of these decisions, rather than semi-automatically forming these decisions based on whether their firms perform above or below their performance aspirations.

Limitations and future research

Like every empirical study, the three studies in this dissertation have limitations that can be addressed by future research. First, in the three studies in this dissertation I use patent data to empirically measure my sample firms' technological capabilities. Although this practice is well-established in the literature, using patent data as a proxy for technological capabilities has inherent limitations. For example, firms do not patent all of their inventions, not all inventions are patentable, and patents differ in terms of their technological significance. Hence patents can only partially represent firms' technological capabilities. Furthermore, patenting rates may be affected by economic conditions, and differ across firms of different sizes as well as across industries (Griliches, 1990). Lastly, an element of arbitrariness is involved in classifying patents to patent classes and in adding citations to other patents by patent examiners. Despite these limitations, being aggregate and quantifiable measures of firms' inventive efforts, patents remain a useful resource for the analysis of firms' technological progress, and are being widely used by management scholars for this purpose (*e.g.* Ahuja, 2000a; Rosenkopf and Almeida, 2003; Rothaermel and Alexandre, 2009; Makri *et al.*, 2010; Vasudeva and Anand, 2011). To reduce the possible impact of these limitations on my analyses, in all three studies in this dissertation I focus on high-technology industries in which patenting technological knowledge is common and important, and include control variables to control for the effects of firm size, industry membership and time-varying economic conditions. Nevertheless, future research can supplement patent-based measures with qualitative evidence to address the limitations of patent data, and increase the rigor of such analyses as those presented in this dissertation.

Second, in chapter 2 I examine firms' alliance formation patterns in terms of partner choice and technological scope as a result of performance feedback, I do not analyze the type of knowledge utilization strategy (knowledge acquisition or complementary specialization) firms implement in these alliances. Examining the type and performance of knowledge utilization strategies in alliances formed as a response to performance feedback is a fruitful future research direction, as this would help uncover the impact of performance feedback on a firm's value-creation both at the single alliance and at the alliance portfolio level.

Third, chapters 3 and 4 I classify the alliances of my sample firms as knowledge acquisition and complementary specialization alliances based on the development of their patent portfolios with respective those of their partners after the alliance formations. Although the literature suggests that patenting decisions are made strategically and observable patterns in patenting behavior are unlikely to unfold randomly, patents are ex-post measures of firms' technological capability development efforts. My analyses therefore rely on the assumption that firms' ex-post patenting activity is in line with their ex-ante strategic goals in their alliances. While there is strong support in the literature for the validity of this assumption literature (*e.g.* Mowery *et al.*, 1996; Nakamura *et al.*, 1996; Colombo, 2003; Colombo *et al.*, 2006), future research can investigate the correspondence between ex-ante indications of strategic goals and patent-based measures to further test this assumption.

Finally, in my analyses in chapters 3 and 4 I consider knowledge acquisition and complementary specialization as mutually exclusive knowledge utilization strategies. Although this approach allows me to empirically distinguish between alternative knowledge utilization strategies and is consistent with the existing research in this area, it can be more realistic to consider these strategies as points along a continuum rather than discrete types of organizational learning, as most alliances are likely to include elements of both types of knowledge utilization. Future research can develop more sophisticated empirical measures to address this issue and to illuminate how both types of knowledge utilization can co-exist in alliances.

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